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FACULTY OF ENGINEERING AND THE ENVIRONMENT

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A Comparative Assessment of Modal Shift Policies (MSPs)

in the Passenger Transport Sector in Korea

by

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ABSTRACT

FACULTY OF ENGINEERING AND THE ENVIRONMENT

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

Doctor of Philosophy

A COMPARATIVE ASSESSMENT OF MODAL SHIFT POLICIES (MSPs) IN THE PASSENGER TRANSPORT SECTOR IN KOREA

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The Marco Polo Programme in the EU was launched in 2003 to stimulate modal shift from trucks to trains or ships. There may be potential for similar programmes in the passenger sector, given the implementation of dynamic Model Shift Policies (MSPs) in the logistics sector. This thesis will focus on the question: 'What is an effective MSP from the car to public transport in the passenger sector in South Korea?', 'What is the best combination of MSPs?', and 'What factors influence the transport mode choice of commuters?" The main MSPs considered in this thesis are: 1) the commuting cost subsidy for public transport users, 2) additional parking fees for car users, and 3) the congestion charges for car users.

In order to investigate the relative effectiveness of these policies, stated preference data were obtained from 767 respondents, who work in the Gangnam area of Seoul, through an online survey that took place in early 2013. A full factorial design was used for the purpose of the survey to estimate the main effects and interactions without correlation. Various binary standard logit models with alternative-specific, generic and covariate variables were developed to identify the effectiveness of MSP and understand what factors affect people's mode choice decisions. In order to overcome limitations of standard logit by allowing for random taste variation, mixed logit models are developed. In addition, through various models both without and with interaction terms, the modal shift effects of the combined MSPs, as well as single MSP, are compared. According to the change of allocation ratio of two combined MSPs (e.g. subsidy 0% : parking 100% → subsidy 10% : parking 90%), the market share of travel mode was also evaluated to understand interaction terms. This research offers numerical evidence of negative modal shift synergy effect for three combinations of MSP.

With a view to forecasting the modal shift effects of socio-economic groups and a more deep understanding of the characteristics of each group, the segmentation methods were used. An equity impact analysis of MSPs has been conducted to obtain the Compensating Variation Per Person (CVPP). In addition, the ratio of the CVPP to the average income of each income group is calculated to judge whether each MSP is a progressive or regressive policy. The expenditure and revenue of MSPs are calculated. In addition, how revenue from MSPs should be spent in order to achieve a better transport system is considered.

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Academic Thesis: Declaration of Authorship

I, DAE SOON PARK,

declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

A Comparative Assessment of Modal Shift Policies (MSPs) in the Passenger Transport Sector in Korea

I confirm that:

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Abbreviations

ASC	Alternative Specific Constant
BRT	Bus Rapid Transit
CBD	Central Business District
CTR	Commute Trip Reduction
CV	Compensating Variation
CVPP	Compensating Variation Per Person
CS	Consumer Surplus
EMBL	Exclusive Median Bus Lane
EV	Equivalent Variation
EV	Extreme Value
HCS	Hicksian Consumer Surplus
HDL	Hicksian Deadweight Loss
IID	Independently and Identically Distributed
IIA	Independence from Irrelevant Alternatives
LOS	Level-Of-Service
LR	Likelihood Ratio
LRT	Light Rapid Transit
MCS	Marshallian Consumer Surplus
MDL	Marshallian Deadweight Loss
ML	Maximum Likelihood
ML	Mixed Logit

MLE	Maximum Likelihood Estimation
MLM	Mixed Logit Model
MNL	MultiNomial Logit
MSP	Modal Shift Policy
OLS	Ordinary Least Squares
PT	Public Transport
RP	Revealed Preference
SLL	Simulated Log-Likelihood
SOV	Single Occupant Vehicle
SP	Stated Preference
TCM	Transportation Control Measure
TDM	Transport Demand Management
TOD	Transit Oriented Development
VMT	Vehicle Miles of Travel

Chapter 1. Introduction

1.1. Research Background

Under the influence of the Kyoto Protocol, climate change is receiving wide recognition from the international community. The scientific evidence points to a significant human contribution towards changing the world's climate (IPCC, 2007, 2001). Due to technological progress and the increased awareness of environment preservation, the concepts of "sustainable development" and "green growth" have emerged as alternatives to the current fossil-based economy. In response to this trend, the Korean government has proposed a national development strategy of "low carbon, green growth" in August 2008. Like other economic sectors, the concept of environmental sustainability has become one of the main concerns in the transportation sector since it is possible to introduce this concept into the transportation sector.

The Marco Polo programme in the EU was launched in 2003 to stimulate the modal shift by freight traffic from truck to train or ship. This positive programme in the EU caused the pervasive introduction of similar programmes in the freight and logistics sector in other countries. To attempt to pursue environmentally-friendly freight transport, the Korean government introduced the modal shift grant scheme from the truck to train or coastal shipping, called Modal Shift Policy (MSP) in South Korea, as an initial project in July 2010. The government subsidized transferable commodities such as containers, steel, cement and limestone on a few routes. The Korean government spent about 8.4 million pounds (up to 2012) to change transport mode in the freight market (Korea government data, 2013). In the atmosphere of pursuing policy change, the general public and policy makers in South Korea have been interested in the concept of MSP in passenger transport.

Due to rapid economic growth and the enhancement of people's standard of living, car ownership and use of cars have significantly increased during the past 30 years in Korea (1980: 1,982,000 cars → 2013.6: 19,160,000 cars, yearbook of construction statistics). The policy, known as "predict and provide" in the UK (Owens, 1995; Bonsall, 2000), of predicting the increasing demand for road space and providing the extra capacity required has been continued until the mid-1990s. Despite the enormous investments in infrastructure and the expansion of road networks, traffic congestion, traffic accidents, air pollution and energy consumption have increased significantly. In order to overcome a limitation of "predict and provide", the notion that transport users should pay their "full social cost" and the necessity of internalising external cost have appeared as a way of solving traffic congestion and pollution. A comprehensive package of policy measures has also been proposed as a more effective way of achieving the need for radical change (Owens, 1995). Therefore, there has been a move from "predict and provide" to "predict and prevent" in terms of dealing with transport problems.

Furthermore, owing to budget constraints and the often disappointing outcome of investments, Transport Demand Management (TDM) has been considered as a practical alternative strategy. As a matter of fact, the Korean government has tried to introduce a wide range of strategies such as the 10th-day-no-driving system, Mt. Nam Tunnel’s congestion charging (as a form of point toll), and Exclusive Median Bus Lane (EMBL) in recent decades. However, although TDM includes a wide range of transport policies such as the reduction of trip generation, time redistribution and trip route change, TDM has not always obtained a very positive modal shift effect. In conclusion, more positive and effective transport policies for the modal shift are needed to solve the traffic problems and environmental concerns satisfactorily since MSPs may be one of the most effective and intensive policies to reduce traffic congestion and air pollution. The research on strategies to shift towards more sustainable modes may significantly contribute to advancing academic perspectives by offering good evidence and new thoughts.

1.2. Research Aims and Objectives

The primary purpose of this research is to investigate the effective modal shift strategies to contribute directly and indirectly to the environmentally-friendly progress and solution of congestion problems in the passenger transport sector in South Korea. For this research, three questions should be addressed. Firstly, why do people choose a particular travel mode and what factors influence the choice of travel mode? Secondly, what is the most effective MSP for the modal shift? Thirdly, what is the best combination of MSPs for more sustainable transport?

One main subject of this research is an investigation of the factors that affect the choice of travel mode to solve traffic congestion and environmental concerns. The reasons why people prefer a particular travel mode and change their travel mode will be critically analysed. Furthermore, the modal shift effects of each MSP, as well as the preference of travel mode across main categorical groups, will be investigated. Since many existing studies used to explain some influential factors in terms of a partial or narrow point of view (Kottenhoff, 1999; Hole, 2004; Nurdden et al., 2007), this thesis will make use of various explanatory factors such as socio-economic, travel, and attitudinal factors in order to better investigate important explanatory factors from comprehensive perspectives.

To discover the most effective MSP, it is necessary to understand which MSP affects the change of travel mode significantly. For this purpose, the sensitivity of mode choices to changing policy intervention will be investigated. Because only a few earlier studies that offer clear numerical evidence exist (Rodier et al., 1998; Whelan, 2003; Lee et al., 2005; Vedagiri and Arasan, 2009; Golub, 2010; Lee, 2011b), this study will provide the numerical calculation process as well as concrete evidence for the modal shift effect of MSP.

The search for an optimal combination of MSPs is needed to create a maximum positive or minimum negative interaction effect (modal shift synergy effect) of MSPs. Diverse interaction models with various explanatory variables will be estimated to understand the interaction effect in terms of effectiveness, equity and practicality. At the same time, to enhance political acceptability, a feasible and acceptable combination of MSPs as a policy package will be reviewed. Since there are relatively few studies on interaction effect of transport policies (May et al., 2004; Habibian and Kermanshah, 2011 and 2013), the research in this field can provide useful evidence and academic uniqueness.

Through a literature review, the definition and characteristics of MSP are investigated to understand exactly MSP. In addition, the concept and theoretical foundation of MSPs will be sought. In the light of the characteristics of MSPs and the influence on modal shifting, some MSPs will be selected as the main subject of this research.

The specific objectives of this study can be summarized as follows:

1. To investigate the key components of MSPs in the passenger sector. To define the concept of MSPs in terms of the theoretical and practical perspectives, diverse MSPs will be explored.

2. To discover the most effective individual MSP and combined MSPs for promoting modal shift. To this end, the following questions will be answered: ‘What is the optimal individual MSP for reducing car usage?’, ‘What is the best combination of MSPs?’ and ‘Can synergy effects occur when MSPs are simultaneously implemented?’

3. To investigate the key factor which affects the choice of travel mode in terms of the effectiveness of modal shift from a private motorized vehicle to a more sustainable travel mode.

4. To explore whether there is a difference between segmented groups in terms of the current preference for travel mode as well as the modal shift effects of MSP or not.

5. To critically analyse the impact of MSPs on welfare change. In order to judge political acceptability of MSP, the following questions will be answered: ‘What amount of consumer benefits or losses will occur when an MSP is implemented?’, ‘Which MSP is a progressive policy or a regressive one?’, and ‘Which group can get a greater consumer benefits?’

6. To develop a proper mode choice model and grasp the characteristics of various models. For this purpose, various models such as standard logit models and mixed logit models with only alternative-specific variables, generic variables, and additional covariates will be explored.

1.3. Scope of Research

The primary aim of the thesis is to investigate what kind of MSP could achieve a greater modal shift effect away from car to more sustainable travel mode. In general, an increase or decrease of sustainable travel mode depends on whether people can be persuaded to change a travel mode, either through the support for sustainable travel mode or penalties imposed on the fossil fuel-consuming vehicles. Therefore, the thesis focuses on the field that can make strong modal shift effects to investigate the most effective MSP.

In general, when it comes to the purpose of the trip, it can be divided into work, school, business, shopping, leisure, social activities, and personal business. As with the various trips, the journey to work can be a main target for pursuing the modal shift, because of its ubiquity and regular patterns on unchanging routes. In theory, it is much easier to consider alternative policies for commuters than for individuals and unpredictable journeys for leisure and other purposes (Pooley and Turnbull, 2000). Leisure and shopping trips have a greater range of options such as reducing the frequency of visits, changing destinations, and altering visiting time than commuters (Marsden, 2006).

A significant increase in car use may come from commuter journeys. These journeys account for the greatest distances travelled on all journeys over 1,300 miles per year (DETR, 1998a, cited in Kingham et al., 2001). In addition, journey-to-work trips account for around 25% of total trips in the US and occur in the peak period (Zhou et al., 2009). In particular, commute trips used to concentrate in the peak period and tend to be single occupant (Horner, 2004). In South Korea, severe congestion tends to arise in the peak period due to commuter transport demands. As shown in **Table 1-1**, the ratio of commute trips to total trips is high. Therefore, the priority of MSP research can be placed on commute trips. This research focuses on commute trips.

Table 1-1. Trip purpose and travel mode in major metropolitan area (Seoul, Busan, Daegu, Incheon, Kwangju, Daejeon, Ulsan) (unit: %)

Trip purpose	Commute	Business	Home	School	Shopping	Leisure	Workplace	Seeing off	Other	Sum
Percentage	18.2	3.0	45.9	9.5	3.5	5.8	0.9	0.8	12.4	100.0
Travel mode	Car	Bus	Train	Taxi	Motorcycle	Cycling	Walking	Other	-	Sum
Percentage	42.2	18.1	16.6	0.9	1.7	2.5	15.7	2.3	-	100.0

* Source: KOTI, 2010.

The scope of MSP contains the modal shift from car to Public Transport (PT), walking, cycling, and car sharing. Feasibility of walking and cycling used to rely on the commute distance and individual’s health. Joshi (1998), and Jones and Bradshaw (2000) indicate that most car journeys are related to the trips that are too far to be walked and cycled. In addition, sharing close neighbourhood and coordinating sharer’s timetable are usually needed in car sharing. Since car sharing sometimes depends on cultural differences in attitude to car ownership and car use, it is difficult to judge how much successful car sharing (car clubs) is (Jones and Sloman, 2003). In Korea, car sharing has been not prevalent because of relatively closed culture and reluctance to rely on other people's intervention. Carpooling used to be limited to close colleagues, relatives and family members because of security problems. Therefore, due to these limitations, the top priority may be placed on the modal shift from car to PT. That is, modal shift to walking, cycling, and car sharing may be complementary to the modal shift from car to PT. PT may be the most appropriate and effective travel mode as a substitute for cars.

1.4. Thesis Outline

This thesis is organised as follow:

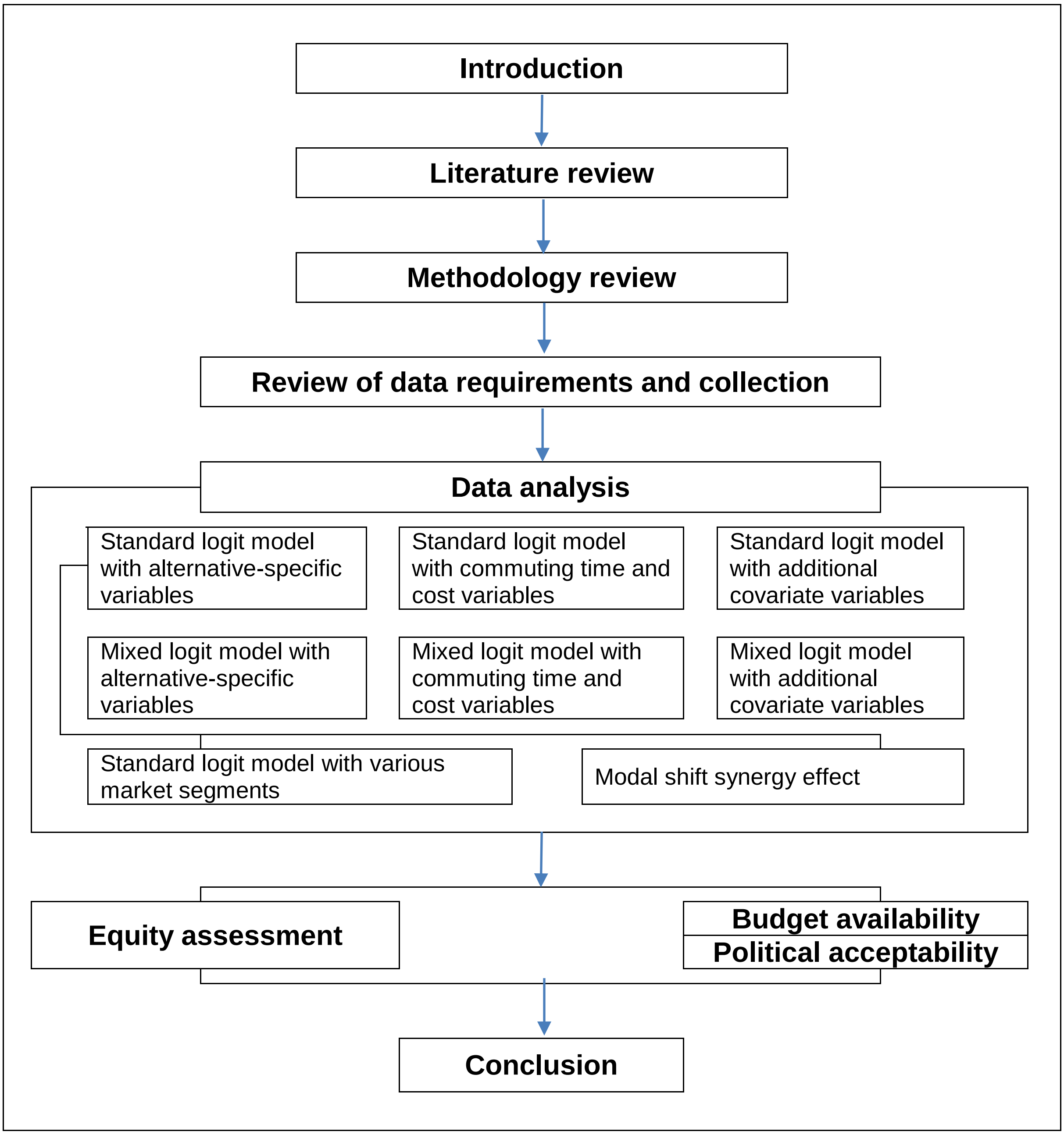
Chapter 1 addresses research background, research objective including the critical research question, the scope of research, and thesis outline. The main point of this chapter will focus on why this research is necessary and what will be carried out how. In Chapter 2, this research explores literature review and the main subject of research, the characteristics of MSP, and the previous criteria on various types of transport policies. The review of research methodologies is dealt with in Chapter 3. In this chapter, modelling tools are identified. In particular, this chapter will focus on the stated preference method, full factorial design, and logit modelling method. Chapter 4 deals with how to carry out online survey location, whether the representativeness of samples is satisfied, and what the meaning and information of survey data is.

Chapter 5 calibrates nine types of standard and Mixed Logit Models (MLMs) with only alternative-specific variables respectively and predicts the modal shift effect of both an individual MSP and the combined MSPs. Chapter 6 reviews the interaction effect of the combined MSPs and comparison of the choice probability curves with/without interaction terms. The modal shift synergy effect is also investigated. In Chapter 7, the application of logit models for market segmentation is illustrated. The method of segmentation analysis, correlation analysis, and segmentation results with socio-demographic and attitudinal variables are presented. The two types of segmentation models are developed to understand the modal shift effects of MSP and to judge the current preferences of travel mode across segments. Chapter 8 assesses the equity impact of the MSPs to judge which income group is a winner or a loser, and to calculate how much benefits or burdens occur. To this end, the Compensating Variation Per Person (CVPP) and the ratio of CVPP to the average income of segmented income group are calculated.

Chapter 9 develops various types of the standard logit models, MLMs with time and cost variables and predicts the modal shift effect of the MSP. In Chapter 10, the standard logit models and MLMs with attitudinal, socio-economic, and travel covariates are calibrated. Standardized models are also developed to understand the relative importance of explanatory variables.

Chapter 11 describes how much revenues and outlay from each MSP can occur, how and for what purpose the revenues of the MSP should be used, and how political acceptability can be obtained. Finally, Chapter 12 discusses contribution, limitation of this research, and suggestion for future study. **Figure 1-1** represents research flow chart to understand clearly main research content and research process.

Figure 1-1. Research flow chart



Chapter 2. Literature Review and Review of Modal Shift Policy

2.1. Introduction

The objective of this chapter is to review earlier studies and materials of Modal Shift Policy (MSP) and to decide the direction of research. This chapter consists of six sections. Section 2.2 reviews earlier studies. Section 2.3 investigates a definition and characteristics of MSP. Section 2.4 determines the three effective MSPs as the subject of research. Section 2.5 presents the theoretical background of MSPs. Section 2.6 classifies transport policies. Finally, Section 2.7 reviews representative MSPs.

2.2. Literature Review

2.2.1. Review of earlier studies

There are many studies on the modal shift effect of a certain TDM as a kind of MSP. However, the subject of transport policies is very different according to the situation, country, trends and interests. That is, since the subject of research usually depends on various circumstances in each country, each case is different from each other.

In the UK, Zhang et al. (2006) researched three types of policy instruments to identify optimal transport strategies and to measure the total welfare of transport strategies. Zhang et al. demonstrated its application to six UK cities such as Bristol, Dundee, Edinburgh, Exeter, Leeds, and Preston. Two types of analysis were reported: sensitivity tests for the effectiveness of policies and optimisations of policy packages such as PT fare changes (− 50% ~ + 100%), PT frequency changes (− 50% ~ + 200%), and cordon charges (0 ~ 10 euros). Zhang et al. recommended all cities to reduce PT fare, to increase PT frequencies, and to introduce cordon charges. In particular, Zhang et al. indicated that a cordon charging was useful for obtaining revenues whereas the optimal lower PT fares and higher frequencies led to a substantial additional financial outlay. The study offered some ideas about the comparison of three economic measures and the level of attributes for this thesis.

Takama et al. (2009) analysed the relationship between parking location and willingness to pay the road user fee, the potential effects of the road user fee, and the park and ride scheme in the Peak District National Park with SP survey techniques. The analysis concentrated on the equity analysis of the road user charging as well as congestion level. Takama et al. indicated that road user charging had great potential to reduce congestion in this area. However, the potential monetary policy tool presented an equity problem because elderly visitors would be more willing to pay the toll and the parking fee at the Information Centre. The research provided the concept of monetary policy tools and a clue of equity assessment for this thesis.

In the US, Golub (2010) studied the impacts on the PT ridership of changes in gasoline prices and service levels. In addition, user economic welfare changes before and after gasoline price changes were calculated. A binary mode choice model between car and PT was used to keep the choice mechanism simple. If a car is faster than PT, an increase in gasoline prices makes lower modal shift effect and smaller welfare loss. Conversely, if a car is slower than PT, an increase in gasoline prices creates higher modal shift effect and larger welfare loss. In addition, the low-income group constructs higher modal shift effect and smaller welfare loss. The various scenarios illustrated significant impacts of travel choice and welfare change under the change of fuel prices. The study gave the concept of assessment for economic measures and pricing policies to this thesis.

In Canada, Washbrook et al. (2006) analysed the impact of road pricing, parking charges, and alternative improvement to reduce demand for Single Occupant Vehicle (SOV) usage in Greater Vancouver suburb. The alternative-specific discrete choice experiment was used with 650 respondents. The choice options were ‘driving alone’, ‘carpooling’ or ‘taking a hypothetical express bus’. Washbrook et al. suggested that financial disincentives for driving alone resulted in greater reductions in SOV usage than increasing measures in the car travel time or PT improvement measures in travel time and cost. That is, improving travel time had a small impact on mode choice whereas an increase in car travel cost had significant effects on car demand. Washbrook et al. described that an effective and efficient way for mode change was the introduction of pricing policies in the regions. This result influenced the introduction of pricing policies in this thesis.

In Sweden, Eriksson et al. (2008) examined three measures such as a raised tax on fossil fuel, improved PT and a subsidy of renewable fuel with SP survey. To analyse factors important for the acceptability, fairness and effectiveness were researched. Eriksson et al. suggested that pull measures (e.g. improved PT and a subsidy of renewable fuel) were perceived to be effective, fair and acceptable whereas push measures (e.g. a raised tax on fossil fuel) were ineffective, unfair and unacceptable. In addition, Eriksson et al. proposed that the combination of a raised tax on fossil fuel and improved PT was more effective than the individual measures. The research showed the importance of political acceptability, fairness and effectiveness, as well as the idea of comparison between pull measures and push measures, for this thesis.

Steg (2005) researched to what extent different motives such as instrumental, symbolic and affective motives were connected with the level of car usage in the cities of Groningen and Rotterdam, the Netherlands. Several explanatory variables such as car attitude, age, income, gender, and annual mileage were evaluated by the attractiveness of different motives and independence. Steg indicated that car commuters were most strongly associated with symbolic and affective motives, and not with instrumental motives. Steg found that respondents with a positive attitude to the car, frequent drivers, younger and male respondents considered non-instrumental motives more valuable than the other motives. The results suggested that many social and affective motives should be considered, besides instrumental motives for car usage. The paper affected the introduction of attitudinal factors in this thesis.

In Israel, Albert and Mahalel (2006) compared the difference in attitudes towards congestion tolls and parking fees through SP surveys. Albert and Mahalel chose three factors, such as toll, cost, and time as travel attributes, and compared four alternatives: (1) to use a car and pay the respective congestion toll and parking fee, (2) to use a shuttle bus or PT, (3) to use a car and park outside of the campus, (4) to use a car but change the arrival time to avoid the toll. Albert and Mahalel developed a Multi-Nomial Logit (MNL) model with individual's socio-economic and the attitudinal characteristics. As a result, 54% of the drivers for the introduction of a parking fee and 72% of the drivers for the introduction of congestion tolls would prefer alternatives to avoid the charge. Since the readiness to pay parking fees was great, the modal shift effect of congestion charges was high during the toll time. In addition, 40% of the drivers would change their journey time under the short operating time of congestion charging. The main finding was that the effectiveness of congestion tolls in reducing demand was higher than parking fees because 48% of respondents were ready to pay additional parking fees.

In Thailand, Dissanayake and Morikawa (2001b) studied the change of modal share for travel mode in respect to vehicle taxation and transit fare reduction support for developing countries. The choice set of transportation modes included bus, car, motorcycle, hired motorcycle, and taxi. A multi-level nested logit model was developed to predict the choice of travel mode and trip chaining. This model was applied to the concept of 'push and pull' policy by implementing a vehicle tax as well as subsidization of PT in Bangkok Metropolitan Region. Dissanayake and Morikawa indicated that congestion reduction policies would create the reduction of vehicle kilometres of travel and air pollution quantities. In addition, Dissanayake and Morikawa proposed that since the tax revenues from the road pricing system were higher than the funds requirement for PT fare subsidy, the government revenue could be increased. The most influential policy was achieved by treating CBD and inner suburb zones separately by different vehicle tax systems. The research offered the necessity of revenue prediction concerning each MSP, review on diverse logit models, and the consideration of policy packages to this thesis.

In Malaysia, Nurdden et al. (2007) compared modal shift effects of three policies: providing park and ride, raising the legal age for driving from the current 18 to 23, and transit improvement by using SP methods. A binary logit model was developed for three alternative modes: car and bus & car and train. For the three policies, the significant factors affecting the choice of travel mode, such as age, gender, car ownership, travel time, travel cost, and household size, were investigated. The most important variables for enhancing modal shift were reduced travel time, reduced walking distance to PT stations, and subsidized fare. The probability of car user switching to PT concerning various travel time and cost was predicted. As travel time, distance from home to PT station, or distance from home to work goes up, car usage increases. This case study showed the usefulness of a binary logit model as a modelling tool to measure modal shift effect of transport policies.

In Iran, Habibian and Kermanshah (2013) compared five TDM measures including three push (‘increasing parking cost’, ‘cordon pricing’, and ‘increasing fuel cost’) and two pull measures (‘transit time reduction’, and ‘transit access improvement’). The choice options were transit with walk access (Walk & Ride), transit with car access (Drive & Ride), transit with taxi access (Taxi & Ride), ride a motorcycle (Motorcycle), taxi with car access (Drive & Taxi), catch a taxi (Taxi), and take a taxi via telephone (Tel-taxi). This study used the SP data of 288 individuals who regularly use their cars to access their job location in the central Tehran area to develop binary choice models. The result showed that pull measures were effective only in the related modes, and cordon pricing had modal shift effect toward ‘Tel-taxi’. In addition, the transit time reduction was significant in the ‘Walk & Ride’. Transit time reduction by 15% resulted in 15.1% mode change to PT. If transit time reduction reaches 30%, 21.4% of drivers would change their modes to ‘Walk & Ride’. In conclusion, Habibian and Kermanshah indicated that aside from ‘Taxi’ and ‘Walk & Ride’ mode, the modal shift effect of these policies from car to other modes were negligible. The research provided the need for research on policy package as well as interaction effect of transport policies for this thesis.

In terms of the modelling tool, McFadden (1976) used the MNL models as disaggregate mode choice models. In the research, “a disaggregate choice model is specified by forming a concrete individual utility function, a probability distribution of a unobserved variable, and a share of each market segment” (McFadden, 1976). McFadden pointed out that the choice of travel mode depended on some socio-economic characteristics and Level-Of-Service (LOS) variables (alternative’s attributes). The individual’s the utility of travel mode might be a function of LOS variables for the travel mode. In addition, a group of individuals with similar observed characteristics and background could be market segments. Meanwhile, McFadden indicated that transportation behaviour might be affected by “total pattern of travel; location of residence and job; purchases of vehicles; frequency of work, shopping, personal business, recreation and other trips; destination of trips; scheduling of trips, mode choice; and route choice" (McFadden, 1976). The results of research showed that the key variables that have important explanatory power were walk time, auto-on-vehicle travel time, travel cost, access time, transfer wait time, PT headways, number of people in a household who can drive, determinants of alternative availability, and income level. The paper provided disaggregate behavioural forecasting methods based on individual's choice behaviour and the idea of market segmentation methods for this thesis. The paper also offered the necessity of research on socio-economic characteristics.

Hoen and Koetse (2014) examined an online stated choice experiment on the preference of Dutch private car owner of the alternative fuel vehicles (hybrid, electric, plug-in hybrid, flexi-fuel, and fuel cell). The choice attributes were car type, purchase price, monthly costs, driving range, recharge/ refueling time, additional detour time, number of available brands/models, and policy measure (e.g. free parking, access to bus lane, and abolishment of road tax exemption). Hoen and Koetse developed the MLM to understand the preference heterogeneity for the choice of alternative fuel vehicles. The results represented improvements on driving range, refueling time and fuel availability could enhance preference for alternative fuel vehicles. In addition, an interaction model uncovered that annual mileage was the most important factor that decides heterogeneity in preference for electric and fuel cell car. The results of the market segmentation analysis suggested that policies targeting specific group might be more effective in increasing the use of alternative fuel vehicles than generic policy measure. As a result, annual mileage, the willingness to pay for driving range, car usage for holidays abroad, and the daily commute are related to the use of alternative fuel vehicles. Hoen and Koetse also estimated the MNL models with interactions between choice experiment attributes and car use characteristics (i.e. annual mileage and commuting, holidays, recharging potential and policy measures, monthly costs, and purchase price). The paper showed the case study of building the MLM and the methods of market segmentation analysis and model estimation to this thesis.

Bhat (2000) compared the MNL model, the deterministic coefficient logit model, and the random coefficient logit model. Bhat researched that an individual's intrinsic mode preference and responsiveness to LOS variables (i.e. travel cost, in-vehicle time, and out-of-vehicle time) affected the choice of travel mode. An individual's intrinsic mode preference and responsiveness would vary on the basis of observed and unobserved individual characteristics. The choice options were 'drive alone', 'shared ride with two people', 'shared ride with 3 or more', 'transit', and 'walk'. The data source came from 520 individuals in the San Francisco Bay Area. This research indicated that congestion charging and parking pricing schemes depend on the use of monetary disincentives for car drivers alone while improvement to PT service may involve frequent service and more extensive route coverage, or introduction of additional express services. All of these policies can be reflected through changes in the appropriate LOS variables. Bhat found that the mean coefficient value of the non-LOS variables in the random coefficient logit model is higher than that in the deterministic coefficient logit model and the random coefficient logit model is more sensitive to LOS variables than the other models. As a result, Bhat indicated the necessity of the research on the MLM as a different sort of logit models allowing for preference heterogeneity of individuals in the logit. The paper offered the estimation method of the MLM to this thesis.

Lindström Olsson (2003) classifies different types of factors that influence the choice of travel mode into six sets of factors: environment-specific factors (e.g. topography, weather, and access to shops), trip-specific factors (reason for the trip, luggage, and errands), transport-specific factors (timetables, parking facilities, and stations), individual-specific factors (age, sex, and income), quality factors (safety, security, and standard of the transport system), measures affecting the choice of travel mode (marketing, communication, mode-specific measures and policy measures) through the review of literature. Although there are some ways of classifying factors, this classification is a more comprehensive classification. However, in many cases, the explanatory factors that influence the choice of travel mode depend on the purpose of research, data collection, and so on. In particular, the number of explanatory factors is usually limited to some extent due to the limitation of data collection. Therefore, this research indicated that the influential explanatory factors should be appropriately chosen to carry out the research efficiently and effectively.

In Korea, Lee (2011a) analysed the relationship between transportation behaviour and either of environmental consciousness or dependence on passenger cars. Lee measured the effect of environmental consciousness on preference behaviour for a car or a train. Lee demonstrated that higher social environmental consciousness resulted in more frequent use of a train whereas higher self-centred environmental consciousness led to more frequent use of a car. The research indicated that environmental consciousness could be an important modal shift factor and a higher preference for cars brought about the increase of car use. Therefore, the research supplied the necessity of research on attitudinal factors as the key factor influencing the choice of travel mode for this thesis.

In addition, Lee et al. (2005) tried to compare the effectiveness of the PT commuting cost subsidy, fuel tax and increasing parking cost through SP survey in Jongno-Gu and Jung-Gu area. The comparison is based on a monthly unit and SP choice experiment was carried out with a fractional factorial design. Sample enumeration method and non-parameter bootstrapping method were used to secure reliability of the empirical result. Lee et al. indicated that the effectiveness of commuting cost subsidy is higher than the other two policies, and the effectiveness of fuel tax is higher than parking fees. Lee et al. also proposed that the increase of parking fee and fuel tax is income-regressive whereas commuting cost subsidy is income-progressive. In addition, Han (2007) compared these three policies in terms of the effectiveness of the modal shift by using market segment method with

SP data. The result represented that in terms of the effectiveness of modal change, the male, the elderly, the rich, the highly educated, and people who take a long travel time are higher than other groups. Han and Lee (2006) also analysed the equity and effectiveness of these three policies. These studies gave the concept of research frameworks, such as the effectiveness of modal shift and equity assessment, to this thesis.

2.2.2. Characteristics and Uniqueness of Research

The earlier studies offered useful insights into the research direction, the basic concept of the framework, modelling tool, and significant implications for transport policies. However, the research that investigates the most effective MSP in the passenger sector is still insufficient in South Korea. This study will investigate not only the most effective MSP but also the most powerful explanatory variables for modal shift. For this purpose, the congestion charging, parking pricing, and PT commuting cost subsidy, as some of the most effective MSPs, will be compared through various standard logit models with alternative-specific variables. In addition, models using only Stated Preference (SP) data or both Revealed Preference (RP) data and SP data will be compared to develop a good model and to investigate the characteristics of models.

Standard logit models with various explanatory variables will be calibrated to understand what factors affect the choice of travel mode significantly. The key explanatory variables will contain attitudinal, travel, and socio-economic factors. In particular, the research on attitudinal factors will be carried out to investigate the relationship between the attitudinal factors and the choice of travel mode. In terms of the method of analysis, the standardized method will be utilized to exactly compare the relative importance of the explanatory variables.

In terms of the modelling tool, various MLMs will be developed to understand the characteristics of the logit model and to calibrate better models. That is, diverse MLMs, accounting for individual's taste heterogeneity of mode choice, will be calibrated to obtain useful insights on flexible models. In particular, diverse MLMs, which contain the interaction terms of the MSPs, with various explanatory variables will be estimated to judge whether the interaction effects of the MSPs are significant in the various MLMs or not. Since there are a few researchers on the MLM in the transport sector (Algers et al., 1998; Train, 1999; Bhat, 2000; Brownstone et al., 2000; Whelan, 2003; Hensher, 2001; Yannis and Antoniou, 2007), the calibration of diverse MLMs can provide useful information and academic uniqueness. Therefore, it is expected that the comparison of the standard logit models with the MLMs can offer new insights of the MLM and a deeper understanding of the characteristics (e.g. strength and weakness) of various logit models.

To understand the interaction effects of the combined MSPs, a full factorial design will be introduced in this thesis. Although there is much research on SP survey, most of them have used only fractional factorial designs due to concern about poor responses. However, due to the full factorial design, more sophisticated assessment can be carried out. The specification of models is based on a daily trip to assess the sensitivity to the level of the MSP exquisitely. Thus, the interaction effect and modal shift synergy effect of the combined MSPs, in addition to the main effect of an individual MSP, will be revealed with the concrete numerical evidence and clear graphs. In addition, diverse logit models with various explanatory variables, including interaction effect variables, will be developed to understand the interaction effect of the MSP in the generic models and covariate models. Furthermore, the relationship between synergy effect and redundancy effect will be investigated. This result is expected to create the uniqueness of this research.

Two types of segmentation approaches, developing a segmented model using dummy variables and segmented models using separated data of segmented groups, will be utilized in order to understand the relative current preference toward travel mode, the modal shift effect of the MSP, and intrinsic mode preferences across segmented groups. To this end, the various factors such as socio-economic and attitudinal variables will be segmented. Since a general picture is that most of the researchers used to choose only one of the two methods, this research may provide useful insights into the two segmentation methods.

An equity impact analysis of the MSP will be carried out to obtain the Compensating Variation Per Person (CVPP). In this evaluation, the two types of segmentation method will be used to compare the differences of CVPP. (The method using the Rule of Half convention will be also used in **Appendix 9**). In addition, the ratio of the CVPP to the average income of each income group is measured to judge whether each MSP is a progressive or regressive policy. This research is expected to provide numerical evidence on consumer welfare change.

Overall, this study will prove that the simple application of the utility functions can measure the amount of consumer welfare change as well as the choice probability of travel mode across each MSP or segmented groups. That is, the simple calculation might make significant results and offer numerical evidence in terms of effectiveness and equity of the MSP. In addition, the calculation of revenues and expenditure according to the change of the MSP can provide the financial perspective of the MSP. Therefore, in terms of effectiveness, equity, finance, and political acceptability, more comprehensive understandings of the MSP can be achieved in this thesis.

2.3. Review of Modal Shift Strategies

2.3.1. Concept of modal shift policies

Even though many researchers often tend to use the term ‘modal shift’, the definition of an MSP hasn’t been clearly developed yet. In terms of official statements, the White Paper on European Transport Policy (2002) emphasized that ‘changing the usage of particular modes is intended to contribute to wider objectives of reducing congestion and pollution’. However, there is no clear definition of MSP.

In the broad meaning, all the policies that have the effect of a modal shift toward a more sustainable transport mode can be called MSPs. In terms of the modal shift effect, modal shift strategies have been widely used since through shift behaviour towards more sustainable modes the reduction of car use is crucial for solving traffic congestion and air pollution. In general, traffic congestion has been recognized as a drag on economic progress, and car use accounts for over 50% of transport carbon emission (DfT, 2011b). Therefore, the concept of modal shift from car use towards more sustainable modes has been commonly used in many countries.

On the other hand, in the very narrow meaning, the term ‘MSP’ has been used for modal shift subsidy policy in the logistics sector. That is, many policy makers in the freight sector are accustomed to understanding MSP in practice as modal shift subsidy policy, especially in South Korea. Therefore, from a historical perspective in South Korea, the concept of MSP may be based on government subsidies for users or operators in order to promote the use of more sustainable travel modes, to reduce the travel cost of transit users or to stimulate the economic competitiveness of more sustainable modes. If modal subsidies result in proportionately higher use of more sustainable travel modes for work trips in peak hour, traffic congestion might be mitigated, potentially with the reduction of CO_2 emissions (EPA, 1998). In addition, since the MSP in the freight sector used to focus on the reduction of CO_2 emissions, the notion of MSP seems to be more environmentally-friendly. Therefore, considering these situations, in many cases, the MSP has been used in practical and historical terms, not academic terms.

In the more limited meaning, MSP can be defined as ‘any action or set of actions aimed at influencing people’s selection of transport mode away from fossil-based transport modes towards sustainable transport modes with direct and immediate effects by non-restrictive methods, particularly with respect to the demand management in order to reduce congestion and pollution’. However, MSP is never static concept but under continuous change. Since the policy making process to achieve the aims and goals is dynamic, the concrete contents of MSP may be changed.

2.3.2. Type of transport demand management

Sometimes, MSP can be included as a part of Transport Demand Management (TDM) measures, particularly in the passenger sector. Accordingly, to understand the area of MSP research, the TDM measure should be sufficiently collated. In general, TDM differs from road-based transport solution to managing traffic. The TDM rejects the conventional ‘predict and provide approach’ and searches for ‘predict and prevent approach’ (Owens, 1995). In terms of the perspectives and researchers, there are various ranges of classification methods. In addition, many TDMs can be combined and mixed in practice. Therefore, the classification can be seen as just a tool for understanding TDM influencing the individual travel behaviour in the transportation sector. Although there are many classification methods of the TDM, a new taxonomy can be suggested in **Table 2-1**.

Table 2-1. New taxonomy of TDM measures

Supply management		Demand management	
Facility supply and expansion	• Bus or subway route expansion and realignment (e.g. new/ faster connections) • Parking-oriented transfer facilities (e.g. construction of ‘park and ride’ outside the urban area) • Pedestrian facility expansion, Bicycle revitalization (e.g. bike and ride, bicycle lanes) • Exclusive bus lane expansion • Elimination or reduction of parking spaces in city centres (in terms of limit supply of parking)	Land use and transport linkage	• Transit Oriented Development (TOD) (e.g. car free development) • Elimination or reduction of parking spaces in city centres (in terms of urban plan)
		Compulsory demand control	• Prohibiting car traffic in city centres (e.g. pedestrianized zones / vehicle van, access restriction zone) • Parking controls (e.g. the 10th-day-no-driving system, weekly no driving day programme, etc.) • Decreased speed limits
		Economic demand control	• Parking pricing • Congestion charging based on a certain cordon • Commute cost subsidy for public transport users (e.g. deduction of tax to employers giving subsidy for PT users, concession to employers paying tax free for company commute buses etc.) • Taxation of cars and fuel • Emission fees • Distance-based charging
Operational improve -ment	• Operational improvement (e.g. optimal frequency of PT, accessibility and transfer improvement, reliable and safe services, comfort improvement etc.) • Fare discount, price cutting of PT • PT information, Intelligent transport system • Bus priority measures • Traffic signal timings favouring non-car mode	Voluntary demand control (smarter choice policy)	• Travel awareness campaigns • Travel information & marketing • Workplace travel planning, school travel planning, Business taxi • Car sharing, car clubs, carpooling, ride sharing • Alternative working patterns (e.g. home working) • Substitution of communications for travel (e.g. teleworking, E-shopping)

* Source: Adopted from Ison and Rye, 2008; Gärling and Schuitema, 2007; Meyer, 1999.
* When supply portion is included in TDM, it can call Transport System Management (TSM).

* There are some redundant items between supply and demand (e.g. elimination or reduction of parking spaces in city centres etc.)

Although TDM often covers the supply side, in addition to the demand side, supply measures should be excluded in the TDM, in the strict meaning of TDM, in order to be true to the term. That is, the term TDM is not suitable for many cases because these are part of transport supply policy or operator's management. It is not TDM in the true sense of the word. However, many measures of TDM in reality include both the supply side and demand side. Therefore, it is difficult to divide both clearly and separately. For example, the extension of 'exclusive bus lane' has been recognized as a representative TDM since this measure can affect the modal shift from cars to buses as well as a reduction of travel time for bus users significantly. It is very difficult to classify it by a particular criterion since it has a wide range of characteristics such as the supply of facilities, the change of people's travel behaviour, and modal shift from car to PT. In this case, 'exclusive bus lane' can sometimes be classified as MSP, TDM, and a supply management measure. However, in this research, although 'exclusive bus lane' has partial characteristics of MSP, it can be classified as a kind of supply management measure in the light of the supply of facilities. In **Table 2-1**, like the classification of Vedung (Vedung and Doelen, 1998), demand management measure can be divided into compulsory measures, economic measures, voluntary measures, and land use and transport linkages. In particular, land use and transport linkages as an urban plan can be an influential measure in view of the influence on travel demand. It can be categorized as a kind of demand management measure rather than supply management measure of TDM.

2.3.3. Difference between modal shift policy and transport demand management, and characteristics of modal shift policy

In a glimpse of the first view, there seems to be no remarkable difference between MSP and TDM in the passenger sector. As defined by Meyer (1999), TDM can be seen as "any action or set of actions aimed at influencing people's travel behaviour in such a way that alternative mobility options are presented and/or congestion is reduced". TDM can be policies designed to promote changes in travel patterns. In this respect, TDM and MSP have similar intentions. In addition, MSP can be sometimes considered as a part of the TDM in the passenger sector because it includes a wide range of measures to change the pattern of travel.

However, the TDM measures are aimed at influencing mode choice, trip length, the frequency of trip and the route taken. The objective of TDM used to include the reduction of transport demand such as the reduction of trip generation and shorter trip distance as well as the change of travel mode. That is, TDM includes the decrease of trip generation, modal shift, time redistribution, and trip route shift.

In the view of the classic four-stage transport model[1], transport demand consists of trip generation, trip distribution, modal split and trip assignment (Ortúzar and Willumsen, 2011; Tavasszy and Bliemer, 2013). Among the four factors, MSP is closely related to modal split or modal choice of individuals. Consequently, the MSP seems to be separable from the TDM in terms of focusing on a modal choice factor more than other factors.

In the logistics sector, the MSP means ‘any action or set of actions aimed at changing from road to rail or waterways to reduce the negative environmental and social impacts of transport’. In terms of the historical perspective, since the Kyoto Protocol calls for industrialized nations to cut greenhouse gas by 5% from 1990 levels by 2008∼2012, developed countries are developing various policies to reduce greenhouse gas in the freight transport fields (Kim et al., 2010). Good examples of this are the Marco Polo programmes in the EU, the Green Logistics Partnership in Japan and freight facilities grants in the UK. More specifically, Marco Polo programmes in the EU to support modal shift, from the road to rail or coastal or inland shipping, were set up for the freight transport in 2003. Under the influence of the Marco Polo programmes, many governments have shown interest in the MSP in freight transport sector so far. In the early stages, MSPs have focused on the modal change to reduce greenhouse gas emissions whereas TDM has been more likely to associate with addressing congestion. Although MSP in the freight sector concentrates on the reduction of CO_2 emissions, the reduction of CO_2 emissions is just a part of several objectives in the TDM in the passenger sector. That is, the TDM tends to search for a more desirable social, economic and environmental objectives whereas the MSPs in the logistics sector used to be emphasized as a relatively eco-friendly policy. **Table 2-2** shows energy use and greenhouse gas emission in Korea.

Table 2-2. Energy use and greenhouse gas emission in Korea

Classification		2001	2004	2009	2014	2019
Vehicle ownership		12,914	14,934	18,213	20,510	21,900
Demand	Domestic passenger (million passenger-km/year)	228,090	236,491	285,264	324,196	363,555
	Domestic freight (million ton-km/year)	137,977	137,701	176,321	228,280	286,257
	International passenger (million passenger-km/year)	77,072	90,146	122,744	155,969	198,232
	International freight (million ton-km/year)	4,739,548	6,217,164	7,570,019	8,227,154	9,515,464

* Source: KOTI, 2007.

[1] 1) The first stage (trip generation): determines the total travel and flow departing from each origin (trip production) and total travel and flow arriving at each destination (trip attraction).
2) The second stage (trip distribution): combines origin and destination in order to form trips, predicts the volume of a trip, and models the choice of movement (Tavasszy and Bliemer, 2013).
3) The third stage (modal split): analyses mode choice and predict market share of travel mode.
4) The fourth stage (traffic assignment): decides route choice and flow propagation, and puts origin-destination travel demand by travel mode on the infrastructure network (Tavasszy and Bliemer, 2013).

Distinct features that distinguish MSPs from other forms of TDM measures should be sought to understand the MSP comprehensively and construct the concept of it. The characteristics of the MSP are considered below.

First, the MSP must have a significant effect on transport mode change. The MSP is fundamentally based on the interaction mechanism between modal shift behaviour and transport policy (Kii et al., 2005). Almost all of the TDM measures have partial effects of the modal shift. However, unless TDM has a major effect of the modal shift, it is not MSP. Since the TDM measures include a wide variety of weak modal shift measures to reduce transport demand, the scope of the MSP should be narrowed into strong modal shift impacts.

Second, the MSP must directly focus on the transport mode change. Only the modal-shift-focused measure is compliant with MSP. Far too comprehensive and indirect transport measures, which have many other effects, have the weak position of MSP. Although some economic measures, such as tax policies to reduce the consumption of goods or obtain more government income, can have the influence of partial transport policy, the increase in taxes on fuel cannot be classified as an MSP because it can be considered as just indirect side effects of financial policy. MSP tends to focus on the transport policy to directly induce the choice behaviour of travel mode.

Third, the MSP is more likely to concentrate on non-restrictive measures, especially economic measures. In terms of history, TDM has the action-forcing nature of transport policy since TDM arises in response to a declining funding base for providing new infrastructure (Meyer, 1999). Therefore, there are many regulatory and restrictive measures in TDM. The concept of MSP can include restrictive measures and non-restrictive measures as well. However, a restrictive MSP can cause the encroachment of individual freedom and the reluctance of the public. Thus, it can bring about the increase of political risk and lack of acceptability unless there are emergency situations or strong necessity for solving severe problems as soon as possible. In the light of political aspect, too strong intervention may be unacceptable whereas market-based measures (Winters, 2000), functioning pricing mechanism and harnessing the market, may be more practical and acceptable since the change of cost structure can create the change of modal choice with less reluctance (Gärling and Schuitema, 2007). Consequently, the MSP is more likely to focus more on non-restrictive measures than the TDM. Therefore, regulatory or disincentive measures may relatively lose ground in MSP rather than supportive or incentive measures.

From a historical perspective, since the MSP has been widely used in the freight sector as a modal shift subsidy policy, the MSP has been based on the concept of pricing policy in transport. At the initial stage, the MSP focuses on a subsidization for narrowing the difference between the profit with/without the policy to increase the user benefit or to decrease traffic emission (Kii et al., 2005).

Therefore, the TDM used to impose several regulatory measures to stimulate modal shift whereas the MSP usually focuses on economic instruments to change travel modes.

Fourth, the MSP may pursue immediate modal shift effect rather than the TDM. Although the concept of MSP can subsume long-term effect of the modal shift, MSP pursues immediate effects because the measures leading to immediate policy effects can obtain strong acceptability of the public. MSP pursues the short-term mitigation of existing traffic congestion. For example, although transport facility improvement or Transit Oriented Development (TOD) can have enormous modal shift effects, it takes a very long time to benefit from it. To address the transport problems effectively and intensively, the policies with fast and prompt effect are needed. In particular, since the evidence suggests that in terms of the short-term PT could have a greater role than infrastructure improvements and institution change, modal shift towards PT can be classified into short term measures (Preston, 2012a). Therefore, the transport policies for gradual and slow change cannot be included in the narrow meaning of MSP. In other words, in the narrow meaning, MSP can be confined to the short term policy compared to TDM.

Fifth, MSP may focus on the demand side policy rather than the supply side policy. The effectiveness of MSP depends on the change of demand volume rather than the change of supply volume (Meyer, 1999). Even though TDM is usually expressed as a demand management tool, many projects focus on the supply side policy in reality. In the true sense of the word, TDM should focus on the demand side policy. Likewise, considering characteristics of the MSP, it should concentrate on the demand side policy. That is, the MSP should be interpreted as a kind of demand side transport policy rather than supply side transport policy. Although the constructions of infrastructure and operations of transport facilities as supply side transport policies are still a major part of TDM, it is desirable that MSP aims at the demand side transport policy. Focusing on the demand side is more compliant with the latest trends in the research of transportation (Ruesch, 2001). Much of latest transport policy logic stems from the abandonment of the concept of ‘predict and provide’ as a method of achieving desirable and possible strategies (Goodwin, 1999). Therefore, considering the latest trends, MSP may give weight to the demand side policy.

2.4. Determination of Comparative Modal Shift Policies

Although there are a wide variety of TDM measures in the passenger sector, the research can be assessed by certain criteria to determine the research scope of MSP. The scope of this research is assessed by the degree of MSP characteristics. The criteria can be represented as follows: ① strong modal shift impact, ② modal-shift-focused measure, ③ non-restrictive measure, ④ immediate impact (short term impact), ⑤ the demand side policy.

Considering the detailed meanings, in terms of 'modal-shift-focused measure', too comprehensive measures that have many other effects may be not included in MSP. 'Short term impact' means that the transport policies for too gradual and too slow change should be excluded in MSP since many government policies are usually required to do it immediately. Consequently, the approximate assessment of the MSP can be conducted as in **Table 2-3**.

Table 2-3. Assessment of MSP characteristics in the passenger sector

Criteria / Type	Strong modal shift impact	Modal-shift-focused measure	Non-restrictive measure	Short term impact	Demand side	Sum
PT service improvement	⊙	Δ	⊙	Δ	×	6
PT information	Δ	Δ	⊙	Δ	Δ	6
Parking control	⊙	⊙	×	⊙	⊙	8
Decreased speed limits	Δ	Δ	×	Δ	Δ	4
Parking fee	⊙	⊙	Δ	⊙	⊙	**9**
Congestion charge	⊙	⊙	Δ	⊙	⊙	**9**
Commuting cost subsidy	⊙	⊙	⊙	⊙	⊙	**10**
Fuel tax (distance-based charging)	⊙	Δ	Δ	⊙	⊙	8
Travel awareness campaigns	Δ	Δ	⊙	×	⊙	6
Travel information	Δ	Δ	⊙	Δ	⊙	7
Car sharing	Δ	×	⊙	Δ	⊙	6
Teleworking	⊙	×	⊙	Δ	⊙	7

* When a factor has a partial effect, it is denoted by Δ (calculation ⊙=2, Δ=1, ×=0)

Although this assessment may be somewhat arbitrary and rough, the commuting cost subsidization, car parking fees and congestion charges can be chosen in terms of the characteristics of MSP.

Table 2-4 shows travel impacts for each type of Transportation Control Measure (TCM)[2]. As shown in **Table 2-4**, employer trip reduction, parking pricing, congestion pricing and land use planning have a major impact compared to other TCMs. Congestion pricing can reduce up to 5.7% of daily Vehicle Miles of Travel (VMT). Land use planning can decline maximum 5.4% in terms of daily VMT

[2] Although TCM focuses on lessening the demand for travel at particular sites, TCM includes many of the types of actions considered as TDM. Since **Table 2-4** includes major TDMs, this data can be used in this research.

whereas parking pricing can go down up to 4.2%. In addition, the employer trip reduction[3] can reduce maximum 3.27% of daily VMT. Through four TCMs, daily VMT can be declined up to 18.57%. Additionally, a daily trips can be reduced by maximum 19.06%. Therefore, the result indicated that effective TCMs can change the traffic situations significantly.

Table 2-4. TCM literature review: ranges of travel impact estimates

TCM (Transportation Control Measure) (%)		Percent reduction in daily VMT		Percent reduction in daily TRIPS	
		Minimum	Maximum	Minimum	Maximum
Employer trip reduction		0.2	**3.27**	0.14	**4.06**
Area-wide ridesharing		0.1	2.0	0.46	1.06
Transit improvements		0.13	2.57	0.58	2.46
HOV lanes		0.23	1.4	0.5	0.57
Park and ride lots		0.1	0.45	0	0
Bike and walk facilities		0.02	0.03	0.04	0.04
Parking pricing	Work	0.52	**4.01**	0.39	**4.02**
	Non-work	3.1	**4.2**	3.9	**5.4**
Congestion pricing		0.2	**5.7**	0.44	**4.2**
Compressed work week		0.03	0.64	0.03	0.5
Telecommuting			3.4		2.8
Land use planning		0.05	**5.4**	0.05	**5.4**
Signal timing		(0.02)	0	(0.02)	0
Incident management		(0.08)	0	(0.07)	0
Smog/VMT tax		0.2	0.6	0.1	0.9

* Source: Apogee Research, 1997.

As shown in **Table 2-5**, parking charges and monetary incentives can have a huge impact of the modal shift from car to PT. The three MSPs are considered as representative economic instruments (SPECTRUM, 2005). Therefore, the three MSPs can be the main subject of research.

Table 2-5. Impact of selected employer-based TDM strategies

Strategy	Details	Reduction impact of employee vehicle trip
Parking charges	Previously free parking	20 ~ 30%
Information alone	Information on available SOV-alternatives	1.4%
Services alone	Ride-matching, shuttles, guaranteed ride Home	8.5%
Monetary incentives alone	Subsidies for carpool, vanpool, transit	8 ~ 18%
Services+monetary incentives	Example: transit vouchers and guaranteed ride home	24.50%
Cash out	Cash benefit offered instead of accepting free Parking	17%

* Source: Seattle government, 2008.

Meanwhile, due to its time-consuming aspect, land use planning is excluded from the main subject of research focusing on MSPs. The employer trip reduction can include parking charges or

[3] These programmes are designed to reduce employee commute vehicle trips. These programmes are sometimes encouraged or required by state or local governments, and sometimes are pursued voluntarily by firms (Boarnet et al. 2014). These programmes include generally employer-provided alternative mode services (e.g. a carpool matching service, vanpool service, car sharing programmes), financial incentives for cyclists, or pedestrian commuters, free or reduced PT fares, or a parking cash-out, alternative work schedules, Information and marketing (e.g. a transit promotion campaign) and so on.

commuting cost subsidies. In many cases, employer trip reduction tends to focus on parking management. However, commuting cost subsidization can be functioned as one of the employer's trip reduction measures. If government stimulates employers to pay employees a part of or all of the PT commuting cost through taxation exemption or central or local government's subsidy, it can act as a representative MSP. In particular, due to the breakthrough of intelligent technologies, the use of commuter's travel cards can be checked by the commuting time in South Korea. In addition, the diversion or abuse of employee's cards or tickets can be prevented by the ex-post facto calculation method.

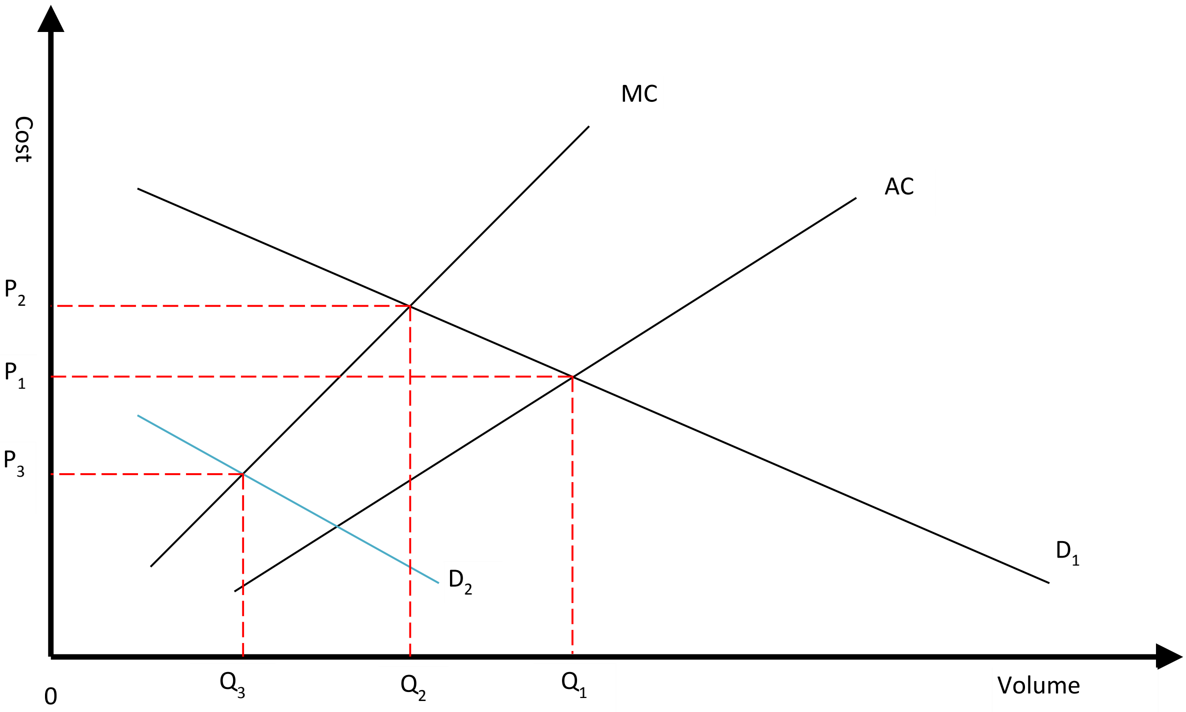
It is widely recognized that the increase of the price of travel for car users would be effective (Meyer, 1999). In particular, Ison (2000) reported that urban road pricing was considered as one of the most effective measures for modal shift. Since the 1960s, both parking fees and congestion charges have often been suggested as efficient ways of reducing travel demand (Ibanez, 1992; Button, 1995; Button and Verhoef, 1998; Alert and Mahalel, 2006). In general, cost internalisation through parking fees and congestion charges could allow a consistent policy framework for tackling transport problems and be a complementary method to existing regulatory policies (European Commission, 1995). In addition, Preston (2008) proposed that PT subsidies are a second best policy but have significant benefits in terms of maximising user welfare. Consequently, comparative research of the three policies can help investigate the most effective MSP in South Korea. Therefore, PT commuting cost subsidies, additional parking fees and congestion charges are determined as the subject of research. The research on the effectiveness of the three MSPs for the modal shift may offer a key clue to the most effective MSP in terms of academic and practical aspects.

2.5. Theoretical Background of Modal Shift Policies

The main objective of the MSP is to reduce private traffic and alleviate traffic congestion. Since traffic congestion causes the occurrence of negative externality or external social cost such as time loss, noise, and air pollution, MSP can be utilized as a way of internalising externality. Traditional economic theory suggests that external social cost can be internalized by introducing MSP such as congestion charging or parking fees to reach the optimal point where marginal social cost equals marginal private cost. This section reviews the academic background to support introduction or implementation of MSP.

2.5.1. Edgeworth paradox

Figure 2-1. Edgeworth paradox



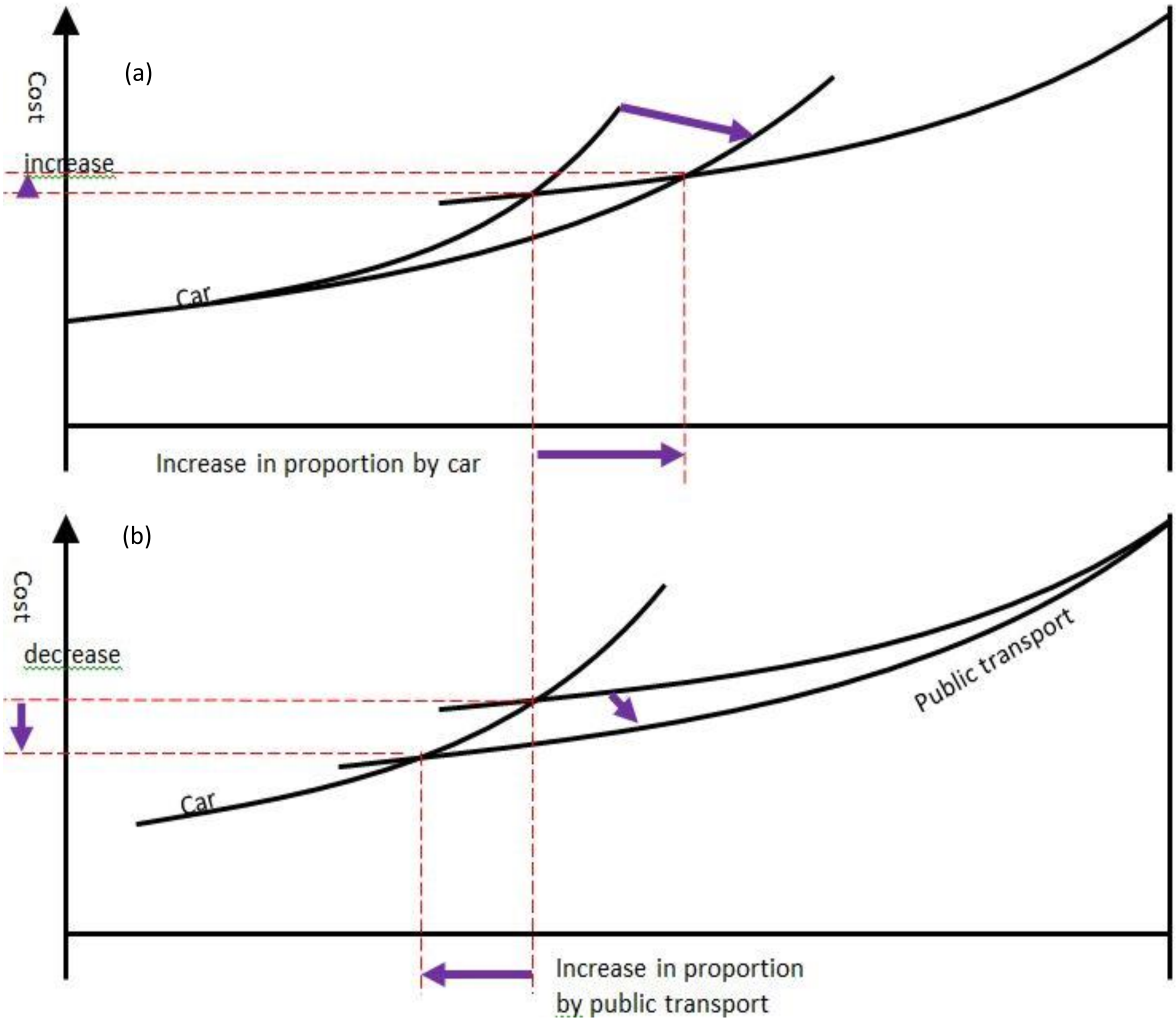
* Source: Lee, 2011b.

The trip cost effect of MSP can be explained by the Edgeworth paradox (Mogridge, 1997). The Edgeworth paradox indicates that the implementation of MSP such as toll or taxation can reduce the equilibrium trip cost. As shown in **Figure 2-1**, the demand and supply curves reach to an initial equilibrium point at Q_1P_1, which is the intersection point of the initial demand curve (D_1) and the average cost curve (AC). If the marginal cost pricing is introduced by MSP, a new equilibrium point is moved to Q_2P_2. The initial demand curve (D_1) shifts downwards to the new demand curve (D_2)

because the increase of cost for car use leads to the decline in the demand of car use. The new traffic equilibrium where the marginal cost curve (MC) and the new demand curve (D_2), meaning reduced demand, are intersected at Q_3P_3 will be converged. As a result, the total social trip cost will be lower at the new traffic equilibrium. Consequently, the introduction of MSP can reduce the equilibrium trip cost. In accordance with the Edgeworth paradox, if car users were levied on road use or parking use, they will shift towards PT use, creating a point where the new equilibrium represents lower trip cost (Lee, 2011). The Edgeworth paradox indicates that the increase of car operating costs by levying MSP such as congestion charging or taxation reaching the intersection point of the marginal cost curve and the demand curve can lead to the decrease of total trip cost in transport market. This result provides the theoretical background of congestion charges and additional parking fees.

2.5.2. Downs-Thomson paradox

Figure 2-2. Downs-Thomson paradox



* Source: Mogridge, 1997.

Downs-Thomson paradox states that if road capacity for car users is increased, the equilibrium trip cost will go up rather than helping to alleviate road traffic congestion. Thomson (1977) maintains that the mode shifts continuously occur until reaching the equilibrium point that there is no difference in attractiveness between car use and PT use.

Suppose that total traffic flow is constant, and modal share of private cars from the left and one of PT from the right. If the road capacity for car users is enlarged, the cost/volume curve for car users switches over to the right. However, the equilibrium point is changed at a higher trip cost than before, as shown in **Figure 2-2** (a). In addition, if the generalised costs of PT users are reduced, the cost of car users will be decreased and the volume of car use will be shrunk, as indicated in **Figure 2-2** (b) (Mogridge, 1997). In contrast, the volume of PT use will increase. This result offers the theoretical background of the PT commuting cost subsidy.

Downs-Thomson paradox indicates that an increase in road capacity could lead to new traffic equilibrium where total trip costs are high. An increase of road capacity and speed results in the decrease of PT traffic. Then, the revenue loss for PT operator, who might raise fares or cut service, occurs (Downs, 1962; Thomson, 1977; Mogrigde, 1997, cited in Denant-Boèmont and Hammiche, 2009).

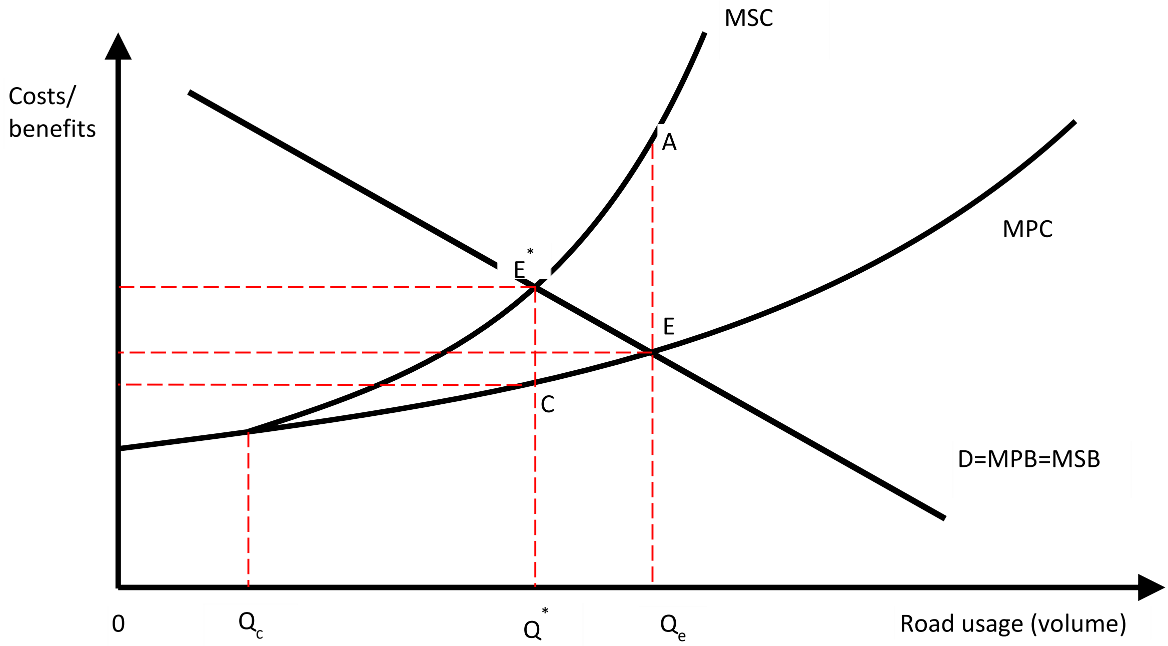
2.5.3. Marginal cost pricing of modal shift policies

The theoretical background of the MSP is based on the principle of marginal cost pricing. In general, the minimisation of a discrepancy between the marginal social cost and the marginal private cost can be achieved by reflecting the social cost into the private cost. Pigou's basic idea is that Pigouvian tax can reflect social cost derived from traffic congestion, air pollution, noise annoyance and accidents into the individual private cost (Verhoef, 2000). To internalise the external social cost of traffic congestion, a congestion tax can be introduced. In this case, the magnitude of tax or toll should equal the external social costs to maximise social benefit.

Suppose that the supply of the road is fixed. In this case, the social cost is the short-run marginal cost and the generalized cost including the travel time and travel cost. D is a demand curve for car users. Demand is the sum of each car user's marginal benefit. The MSC implies the marginal social cost curve of car users, and ASC is the average social cost curve of car users. At the initial stage, for an individual car user, the marginal private cost (MPC) is equal to the average social cost (ASC). In **Figure 2-3**, for section ($0-Q_c$) where all users can use the road without traffic congestion, the trip cost per car is the same. However, if the excessive traffic beyond Q_c occurs, traffic congestion will exist. It means that the marginal social cost (MSC) exceeds the average social cost (ASC = MPC) due to the traffic congestion. In this case, external diseconomies lead to the increase of the marginal social cost.

An initial equilibrium point will be arrived at E, where ASC and D intersect. At this point, the traffic volume Q_e will be determined. At the traffic volume Q_e, the marginal social cost (Q_eA) on the marginal social cost curve (MSC) exceeds marginal benefits, meaning consumer surplus (Q_eE). A new equilibrium point will be reached E*, where MSC and D intersects (Rouhani et al., 2014). This point is the optimal equilibrium point, where the marginal social benefit (MSB = MPB = D) is equal to the marginal social cost (MSC) (Verhoef, 2000). In terms of the traffic volume, Q* is less than Q_e, where demand and supply intersect. This socially optimal situation can be achieved by the implementation of MSP such as congestion charging or parking pricing at the level of external diseconomy (E*C). That is, the increase of the average social cost (ASC) resulted from the implementation of the MSP could lead to the decrease in demand of car users. Thus, since this result can reduce the marginal social cost (MSC), the appropriate traffic volume (Q*) would be achieved (Chung et al., 2006; Lee, 2011).

Figure 2-3. The marginal cost pricing and car usage



* Source: Verhoef, 2000; Rouhani et al., 2014.

2.6. The Classification of Transport Policy

2.6.1. Traditional classification of public policy

Lowi (1964, 1972, 1985) proposed the classification of four types of public policies (see **Table 2-6**). It is expected that distributive policies and constituent policies can easily obtain political acceptance rather than regulatory policies and redistributive policies since the former gives benefits, authorities, powers, or privileges whereas the latter levies burdens, impositions, or obligations.

Table 2-6. Categorization of public policy

Author	Type	Context	Example
Lowi (1985)	Regulatory policy	Impose obligations and sanctions to influence the activities of citizens and companies (restrict and control)	Rail safety law, road traffic law
	Distributive policy	Distribute service and benefit as patronage and subsidy, not impose obligations (public land and resource policies, R&D, labour and business policies)	Infrastructure policy, PT cost subsidy
	Redistributive policy	Allocate benefits and costs by transfer from one group to another (redistribution of income by taxation)	Congestion charge, parking fee
	Constituent policy	Confer powers or jurisdictions: rules about rules and authority (establishment of governance institutions)	Establish new transport agency

From this classification, congestion charges and additional parking fees can be classified as a redistributive measure that radically shifts distributions of costs and benefits (Sørensen et al., 2014). However, redistributive measures can cause political reluctance. Meanwhile, PT commuting cost subsidies can be categorized into a distributive policy. Due to the provision of economic benefits, this policy will be warmly welcomed by local citizens. However, there are some problems such as budget constraints and lack of beliefs in the effectiveness of modal shift. Although this classification is the most commonly used method, the ambiguous criteria, sometimes, are issued.

2.6.2. Classification of authoritative power

Etzioni (1975) classified authoritative power into three forms: (1) coercive power, relying on physical sanctions or threat; (2) remunerative power, drawing on control of resource allocation; and (3) normative power, depending on persuasion, manipulation, and suggestion (see **Table 2-7**). Coercive power is dependent on fear, suppression, punishment, threat, and physical violence. In addition, remunerative power subsumes the allocation of money, material resources, and services functioning as rewards and incentives while normative power includes symbolic nonverbal performances, the transfer of knowledge, moral suasion, exhortation, and other persuasive action to influence over acceptance. In aspect of this classification, the three MSPs are remunerative power.

Table 2-7. Etzioni's threefold classification of power

Power (control)

Coercive	Remunerative (Utilitarian)	Normative (Persuasive, manipulative, suggestive)
Physical sanctions	Material resources, salaries, wages, commissions, contributions, services, commodities	Symbolic rewards and deprivations

* Source: Etzioni, 1975 (cited in Vedung, 1998).

2.6.3. Sticks, carrots and sermons

On the influence of Etzioni’s classification, Vedung (1998) suggested a set of three categorical policy instruments: “sticks” (economic disincentives and/or regulatory constraints), “carrots” (economic incentives), and “sermons” (information). His classification is based on the corresponding power such as coercive power, remunerative power and normative power (see **Table 2-8**). PT commuting cost subsidies can be categorized into carrots whereas the congestion charges and additional parking fees can be classified as sticks.

Table 2-8. Twofold classification of governance tools

Tools of Government

Negative (restraining) Penalties Stick (punishment, costs) Negative sanctions	Affirmative (promoting) Incentives Carrot (rewards, benefits) Grants, tax exemptions, facilitative measures

* Sources: Bernard, 1939.

2.6.4. Regulatory, economic, and informative measures

From the classification of Vedung, regulatory measures can be accepted as rules, directives and standards that oblige people to behave in a certain manner. These measures can be divided into repressive measures and stimulative measures. Economic measures are related to providing or taking away of material resources as various forms of taxes, subsidy or the provision of transport infrastructure. Informative measures include dissemination of knowledge, persuasive reasoning, and exhortation problems to influence the public to do some desirable things (Vedung and Doelen, 1998; Cooksy et al., 2009). In terms of this classification, the three MSPs can be classified as economic measures. PT commuting cost subsidies can be categorized into economic incentives while congestion charges and additional parking fees can be classified as economic disincentives.

2.6.5. Primary measures and ancillary measures

To clearly understand the concept of policy packaging, the concept of primary measures and ancillary/secondary measures can be used. In terms of intervention’s effectiveness, immediate effectiveness and collateral effectiveness can be divided (Givoni et al., 2013). Primary measures are actions considered first and used directly to achieve the policy objective. Ancillary measures can play secondary or indirect but important role in the process of policy packaging (Givoni, 2014a; Justen et al., 2014a). To overcome policy barriers, and to enhance the effectiveness of primary measures or to mitigate unintended side effects of primary measures, ancillary measures can be used. Ancillary measures contribute to the efficiency of policy packaging by increasing effectiveness and implementing the ability of all-round policy for achieving the objective. In terms of this classification, all the MSPs can be primary measures or ancillary measures. If there is a direct effect on the intended objectives, any policy can be categorized into primary measures. For example, if congestion charging is a primary measure to solve congestion problems, a PT commuting cost subsidy would be an ancillary measure to mitigate an inequitable problem and increase public acceptability.

2.6.6. Pull measures and push measures

Vlek and Michon (1992) proposed that according to the degree of coerciveness, the categories of TDM can be ordered from more to less coercive such as physical changes; law regulation; economic incentives; information, education and prompts; socialization and social modelling; institutional and organizational changes (Scott, 2002).

Also, Steg and Vlek (1997) classified TDM on the basis of the coerciveness toward mode change, and categorized TDM as push or pull measures. Pull measures are travel measures to encourage alternative use by making them attractive to car users. These measures cover the park and ride schemes, improved PT services, public information campaigns, TOD, and subsidization. In contrast, push measures are those that discourage car use by making car use less attractive (Habibian and Kermanshah, 2011). Push measures restrict people’s freedom of choice (Steg and Tertoolen, 1999). These measures contain cordon pricing, increasing parking fee, a tax on cars and fuel, and banning non-commercial traffic from city centres. Although this classification is similar to the concept of ‘sticks’ and ‘carrots’, dynamic aspects, through focusing on the methods to achieve the policy objective, may be emphasized. From this classification, PT commuting cost subsidies can be classified into pull measures whereas additional parking fees and congestion charges are categorized as push measures. This research is composed of one pull measure and two push measures.

2.6.7. Hard measures and soft measures

TDM measures can be categorized as hard measures (structural interventions) and soft measures (psychological interventions) (Fujii et al., 2001; Cairns et al., 2004; Graham-Rowe et al., 2011). Hard measures are travel measures to modify the physical and legislation structure that regulates travel behaviour or provides incentives for the policy objective. Hard measures include fiscal measures, provisions for alternative modes, and regulatory measures such as fuel taxes, speed limits, emission standards and road use charging. Soft measures are travel measures to focus on voluntary change that changes beliefs, perceptions, and attitudes. Soft measures contain a range of marketing and management measures such as travel awareness campaigns, workplace and school travel plans, personalised travel planning, the PT information and marketing, car sharing schemes, teleworking, and teleconferencing. More Specifically, since soft measures emphasize on management and marketing activities rather than operation and investment, soft measures are less costly and may be more public acceptable than hard measures. However, hard measures seem to be more effective than soft measures since enforcements by the authority are at force (Roo and Silva, 2010).

According to Givoni's classification, in many cases, hard measures can be used as primary measures, whereas soft measures can be used as ancillary measures. However, many soft measures can also be primary measures to overcome congestion problems. For example, a car sharing scheme can be primary measures to reduce driving alone. In this case, car sharing campaigns can be an ancillary measure.

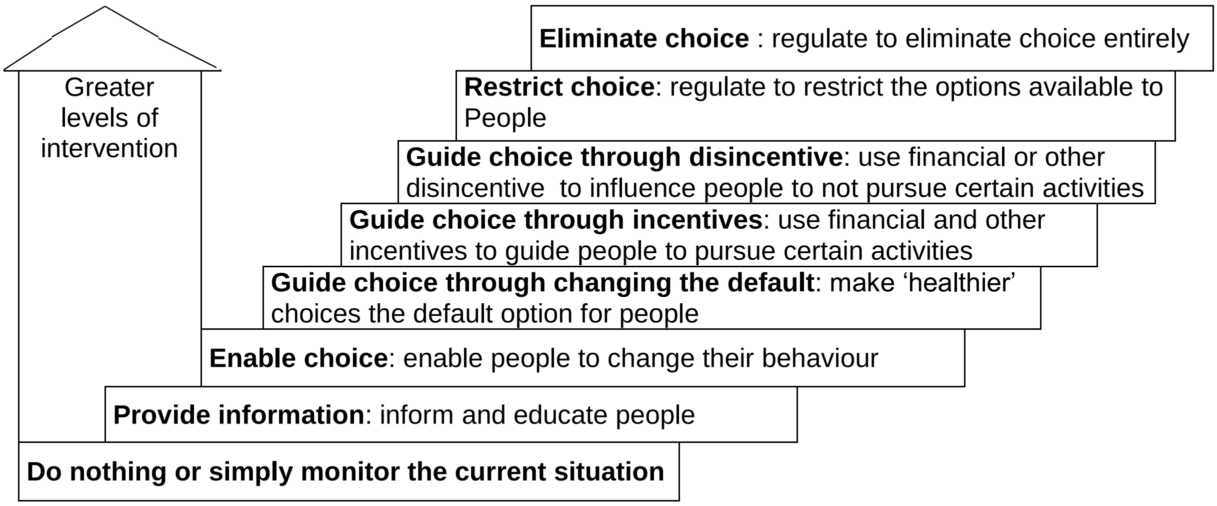
2.6.8. Supply policy and restriction policy

From the perspective of supply and restriction, TDM can divide into supply policies and restriction policies. Supply measures are measures of providing transportation facilities or expanding transport modes whereas restriction measures are measures that alter or reduce the travel demand. Supply measures contain the provision of Bus Rapid Transit (BRT), EMBL, Transit Facility Expansion (TFE), Bus Information System/Bus Monitoring System (BIS/BMS), Business Taxi (BT), Bicycle Revitalization (BR), and Pedestrian Priority Zone (PPZ). On the other hand, restriction measures include parking cap, parking fare policy, resident priority parking, weekly no driving day programme, congestion fee, Vehicle Quota System (VQS), and access restriction zone. In general, restriction measures tend to apply to the country that has high density of population and well-equipped PT facilities, whereas supply measures tend to apply to the country that has low density of population and poor PT facilities.

2.6.9. Ladder of intervention

In terms of the intense level of interventions, TDM measures can be classified as **Figure 2-4**. The intervention ladder offers a tool for thinking about the acceptability and justification of different public policy initiatives, focusing on the degree of invasiveness of the policy objective. In terms of theoretical perspective, the higher the rung on the ladder at which the policy maker intervenes, the stronger the justification has to be. This classification indicates that policy intervention at higher intense level should have stronger justification and clear causes that gain the acceptance of the public. Weak justification can cause resistances or barriers against the implementation of policy. Although his classification is similar to Vlek and Michon's proposition, a more clear and easy concept about acceptability and justification by the intense level of intervention is provided.

Figure 2-4. Ladder of Interventions



* Source: DfT, 2011a (cited in Preston, 2012a)

2.6.10. Application of the research

According to Steg and Vlek's classification, the MSPs in this research are composed of one pull measure and two push measures. That is, PT commuting cost subsidies can be classified as pull measures whereas additional parking fees and congestion charges can be categorized as push measures. Meanwhile, by Vedung's perspective, the PT commuting cost subsidies can be classified as carrots, whereas additional parking fees and congestion charges can be categorized as sticks. In addition, in the light of Cairns's category, the three MSPs all are categorized as hard measures, not soft measures. The research on various combinations of transport policy can provide useful information on the implementation of policy packages.

2.7. Review of Individual Modal Shift Policies

2.7.1. Congestion charging

Congestion charging has been the subject of serious consideration in many countries. New technologies have been developed to enable such schemes to be implemented efficiently and effectively (Balcombe et al., 2004). Congestion charging can be the most effective policy, which is suitable for specific regions suffering from traffic congestion, and a means for financing new transport project (Langmyhr, 1999). The theoretical first-best model of marginal congestion pricing cannot be applied, but second-best cordon tolls can be adopted with the positive effect (Santos, 2004). Güller (2002) indicates that almost all interviewees confirm that people are willing to pay for gains in travel time. The practical and effective way of reducing travel time can be congestion charging.

London introduced an area licensing scheme for the centre in 2003. In a comparison with before (2002) and after (2003) the introduction of this scheme, London experienced a 34% reduction in cars from the impact of the congestion charge on traffic in the charging zone (Leape, 2006). Singapore also introduced an area-wide pricing scheme in the mid-1970s. The introduction of charges in Singapore reduced vehicle volumes in the city centre by 45% (Washbrook et al., 2006). Several cities in Norway such as Bergen, Oslo and Trondheim developed pricing cordons around their centres to finance road building purpose. Percentages of revenue were earmarked for the PT safety and environmental measures. In addition, Stockholm in Sweden introduced a cordon toll charging in & outbound trip in 2006 (Lee, 2011).

In South Korea, although a passage toll system (route-based scheme) as congestion charging was introduced into Nam Mountain 1 and 3 tunnels in 1996, there is no area-based charging system (e.g. CBD cordon scheme). However, in recent years, the extensive introduction of Central Business District (CBD) cordon has been debated as one of MSPs or urban attraction strategies to increase the amenity of the CBD for residents and visitors (Marshall and Banister, 2000) due to severe traffic congestion problems.

2.7.2. Park pricing policy

Too many people are suffering parking problems, such as parking space constraints and the cost of parking when driving in urban areas (Lumsdon et al., 2010). In the past, to solve parking problems, many governments used to focus on providing sufficient parking spaces. However, some researchers indicated that the phenomenon of vehicle travel induced by new parking spaces is similar to vehicle travel induced by new road capacity (Hensher and Button, 2003). Thus, these days, many governments have already recognized that the provision of parking space in the CBD can trigger automobile-dependence travel patterns and bring about severe traffic congestion. Consequently, the constraint of parking and the increase of parking price are used as representative TDMs as well as a second-best solution for addressing congestion (Ison and Rye, 2006).

However, although the constraint of parking facility provision can be the strong TDM to reduce transport demand in urban areas, an excessively strong parking constraint can affect town centre vitality and trigger a loss of urban attraction (Marsden, 2006). The strong regulation can be excessive restrictions on individuals' freedom as well. Since the cost of parking equals 75% of the car commuting cost (Shoup, 1997; Hole, 2004), the increase of parking fee may be justified to reduce car use. Parking pricing may offer direct signals to people on the cost of driving.

In a view of spatial development and historical perspectives, most North American metropolitan areas are characterized by low-density employment sites with abundant free parking. Furthermore, declining transit system investment and population dispersion into suburbs has led to a decreased transit system efficiency and continued high automobile dependence (Washbrook et al., 2006). In this context, most North American metropolitan areas can be classified as high automobile dependence cities (Newman and Kenworthy, 1989). Automobile reliance, low-density suburban land-use patterns, and a modest PT service have the potential to discourage commuters to use PT. On the other hand, city centre in London is severely congested: automobile mode share in the centre was only 12% before the introduction of charges; parking charges were already extremely high; and an array of frequent and efficient transit, subway, rail and taxi services are available to and within the centre (Washbrook et al., 2006). The low ratio of automobile mode seems to be partly due to the long scheme of parking space reduction in the CBD area and congestion charging in London. Therefore, city centre in London may have changed from automobile cities into PT cities and walking cities. The Transport Act 2000 has enabled local authorities in England and Wales to impose levies on workplace parking spaces provided by employers (Balcombe et al., 2004). In terms of high intensity of land use and well-established PT, Seoul seems to be similar to London. However, Seoul has not changed the structure of its city and has not introduced the reduction of parking space in the CBD area and cordon congestion charging scheme.

In conclusion, there are some ways in which a parking policy can be used as a TDM tool. Parking policy can contain limiting the number of available spaces, increasing parking fees, and changing the mix of short and long-term parking spaces available. However, considering the negative effect of the constraint on the provision of parking spaces like damaging the attractiveness of the city centre, the increase of parking expenses can be a practical policy to reduce car use.

2.7.3. PT commuting cost subsidy

In the US, there is a growing trend to try and persuade employers to subsidise their employee's use of PT. In addition, in the UK and the US, there have been moves to restrict employer support for cars such as a parking fee subsidy and free parking for car users. Various schemes such as providing PT travel cards or vouchers have been developed. However, the effect of these schemes has had a minor impact so far, since the size of the support is too small (Balcombe et al., 2004).

The central government in the US has offered tax exemptions for transit passes, commuter highway vehicle and qualified parking. According to tax law, employers can deal with PT support for employees as a form of business expenditure. However, on average, less than 15% of employers offer commute benefits (Zuehlke and Guensler, 2007). Meanwhile, Washington state government has tried to implement Commute Trip Reduction (CTR) programmes since 1991. The CTR law was aimed at reducing traffic congestion, air pollution and petroleum consumption through employer-based trip reduction programmes. The government allowed employers to give commuting cost grants. Employers can obtain a tax exemption for the financial incentives that they gave employees.

The adoption of travel plans by employers in the UK is an important element of the Government's integrated transport strategy outlined in the 1998 Transport White Paper, 'A New Deal for Transport: Better for Everyone' (DETR, 1998b). Meanwhile, the Scottish White Paper (Scottish office, 1998), 'Travel Choices for Scotland', was published and also features travel plans as important transport policy. The government has been committed to encouraging existing organisations to take up travel plans. Local authorities have been required by the DETR to put in place strategies for encouraging local organisations to adopt travel plans. For example, Fife Council investigated the potential of PT season ticket discounts for staff. In Gyle, New Edinburgh Park included discount bus tickets and bus services, on a temporary basis, paid for by the company as a travel plan. Historically, any employer contributions to employee's commuting cost have been subject to personal taxation. It had an impact on travel plans and on the number of organisations willing to implement potentially taxable measures. However, the UK government has been about to consult on the possibility of making employer contracts to carry employees on local bus services no longer taxable (Rye, 2002). In Germany, tax relief on commuting costs is long developed as a lump sum deduction or deduction based on the actual cost of PT or mileage rate for a car. From 1992, a special tax exemption for employer-provided 'Job Tickets' for use on PT in some area of Germany has been introduced (Potter et al., 2006).

In South Korea, there is no PT grant for commuters. Therefore, commuting cost subsidies for commuters can be introduced to reduce transport dependence on the car. It is worthwhile researching the introduction of a commuting cost subsidy in South Korea as a commute trip management.

2.7.4. Fuel pricing

Fuel pricing policy has been placed on either the general taxation measures as an economic policy tool or TDM as an attempt to make road users pay the true costs of utilizing the road network (Woodburn, 2007). In the theoretical perspective, there is a strong link between the tax base and the external cost. Thus, it is desirable that the social or external costs should be reflected in the prices. The fuel tax is the easiest way to reflect external cost on consumers according to the use of roads. However, it seems to be evaluated that the effect of mitigating traffic jams is very low since the fuel tax has more impact on other trips than commute trip. Some researchers indicate that the increase in fuel price does not bring about the decrease of transport demand in the long term. In addition, many studies indicate that the elasticity of travel demand regarding fuel pricing in the short term is low (Albert and Mahalel, 2006). As a result, fuel pricing has many doubts about effectiveness as one of TDMs. In general, fuel taxation has an enormous effect on the economic situation. In other words, fuel taxation has been placed as a macroeconomic policy, not a transport policy. The increase of fuel tax will eventually result in the increase of overall consumer price as well as the increase in fuel price. The worry of the negative outcome against overall economic situations may be considered by the public and politicians. Furthermore, fuel tax revenue accounts for about 5.9% of the total government revenue in South Korea (Ministry of Land, Transport and Maritime Affairs, 2011). The fuel tax revenue is more than the revenue from customs duty (5.4%). The request for a decrease in fuel tax has continuously been brought up from the industrial sector since 2008. In consequence, the political acceptability of a fuel pricing is likely to be less than other TDM measures in South Korea.

2.7.5. Public transport improvement

Improvement of PT service quality may strongly encourage people to switch their mode. In addition, to enhance the attractiveness of the town centre area, improving the PT facilities and enhancing PT service quality are certainly needed. A frequent, reliable and convenient PT system may be able to attract a significant number of people from their car (Kingham et al., 2001). However, the BBC survey found that better quality vehicles, improved security, and better information will have a more limited impact on PT even though the majority of respondents would travel less by car if the PT services were better (MORI, 1999, cited in Kingham et al., 2001). This result seems to indicate the lack of direct interaction between PT use and improvement in the quality of PT.

In South Korea, the subsidy for the PT operators such as bus companies and subway companies has been paid by the government as an operational deficit compensation or subway construction subsidies. However, there is no subsidy to enhance operational improvements such as improving access to the

PT facilities, increasing transport frequency and constructing the new equipment. Therefore, more support for the improvement of PT from the government is needed to stimulate the use of PT. However, since the improvement of the quality of PT service has a wide range of sectors such as frequency, reliability, convenience, security, and so on, practical approach for each section is necessary.

2.7.6. Car sharing

Car sharing has real potential as a way of shifting travel mode from single occupancy car use. The concept of car sharing is based on the distinction between automobile access and ownership. Car sharing divorces the notion of automobile use from ownership by providing people with convenient access to a shared fleet of vehicles, rather than a single privately owned one (Katzev, 2003). It is a good way to lessen automobile use. However, finding car share partners or organizations is a very important factor, but a very difficult thing. In South Korea, the present is the initial stage of introduction. Therefore, it may be a kind of supplementary MSP, not a major MSP.

2.7.7. Promotion of cycling to work

Under the influence of popularity of the sustainable transport mode, the public has recognized cycle as an excellent alternative vehicle. The cycle has various benefits such as low cost, relative speed, flexibility and the enjoyment of exercise (Pooley and Turnbull, 2000). In particular, many people who live close enough to cycle have got interested in cycling to work. However, if they do not live close enough to cycle, they are less likey to be interested in cycling as an alternative transport mode. According to Kingham et al. (2001), improving cycle routes and changing facilities would encourage a relatively small percentage of people to cycle to work. Consequently, there is an obvious limitation in the wide applications. In Seoul, especially, cycle routes and facilities are lacking, and the connections between routes are very poor. As a result, many residents in Seoul have thought about cycling as a very dangerous mode. Therefore, unless well-established cycle routes are provided, the increase of cycle use has limitations in South Korea. In addition, there is a fundamental limit to the widespread introduction of the cycling system because of differences in the contour of the terrain.

2.7.8. Transit-Oriented Development

The transport & land-use coordination measures can be defined as the integration of transportation and land use in the neighbourhood and regional area. The well-equipped transit development of regional hub with high density, concentration and mixed land use can reduce trip generation frequency, trip distance and car use (Black, 1981). The timescale over which sustainable mobility might be realized is similar to the turnover of the building stock (about 2% per annum). However, decisions on the location of new housing will have a single dramatic effect on travel patterns, and these effects will influence over the lifetime of this housing (Banister and Hickman, 2006, cited by Banister, 2008). The strong connection with transport & urban planning may bring about the enormous change of urban travel patterns. Consequently, TOD can be a fundamental solution. However, the TOD takes a substantial period to attain the effect of the change.

2.7.9. Park and Ride

Park and ride can achieve modal shift effect by intercepting cars on the edge of urban areas and enhance the use of PT from car parks. In the case of the City of Bristol, for over half of the users, the park and ride trip had replaced a car journey (Marshall and Banister, 2000). However, according to Parkhurst (2000), the main effect of Park and Ride scheme is traffic redistribution, and their role in traffic restraint policies is unlikely to be directly one of traffic reduction. Thus, this scheme is likely to focus on reducing car travel and traffic congestion in the CBD, not outside of urban areas. Therefore, the Park and Ride scheme has a partial modal shift effect.

2.7.10. Technological innovation

The role of technology is important because it significantly influences the efficiency of the transport and introduction of the new policy. A combination of technological innovation and behavioural change can widely contribute to the change of travel patterns and environmental protection. However, although the best available technology can be used in the transport sector, technology policy in itself has been not recognized as TDM or MSP.

2.7.11. Others

Providing information, teleworking and travel awareness campaigns can be MSP. However, these measures not only take a great deal of time but also can be recognized as an indirect policy. Sometimes, these measures are needed to coordinate and change a great many aspects to introduce them as one of MSPs.

In the meantime, the provision of BRT and EMBL can have a big attractive effect through the reduction of travel time. However, the success of the introduction of this scheme depends on the width of road and junction situation in the certain area. In many cases, the possible area can be limited on the wide road.

The provision of heavy rail (subway, metro), Light Rapid Transit (LRT), Personal Rapid Transit (PRT) and trams system are representative supply policies. However, in many cases, the construction of infrastructure has resulted in the severe budget deficit and operational deficit because of the excessive provision derived from the estimation of excessive travel demand in South Korea. The LRT line between Yong-in and Su-won city and the LRT line between Kim-hae and Sa-sang in Busan are representative failures. Although the provision of the PT facilities is important to improve the travel situation in the long periods, the more careful consideration is required to prevent a waste of money.

2.8. Summary

In this chapter, literature reviews are carried out to obtain the key idea of research. In addition, the review on MSP is conducted to provide a deeper understanding of the characteristics of MSP. According to the prior assessment on the characteristics of the MSP and the effectiveness of modal shift, the three MSPs are determined as the main subject of the research. In addition, the theoretical background of the MSP such as Edgeworth paradox, Downs-Thomson paradox and the principle of marginal cost pricing provides the validity of the economic policy intervention. The reviews on representative MSPs offer various information on each MSP, main issues, and new trends. The classification of transport policy is reviewed to develop the basic frame of policy packages. In particular, considering push and pull strategy for searching for effective policies (Dissanayake and Morikawa, 2001b), the research on the combinations of the MSPs can provide good implication or evidence on synergy effect of transport policies.

Chapter 3. Review of Research Methodology

3.1. Introduction

The principal objective of this chapter determines the main research method. This chapter consists of six sections. Section 3.2 presents a short overview of research approach. Section 3.3 determines alternative-specific variables and explanatory variables. Section 3.4 introduces a full factorial design. Section 3.5 determines the survey area. Section 3.6 determines sample size. Section 3.7 explains modelling tools such as the standard logit model, mixed logit model, and nested logit model. Section 3.8 discusses hypothesis testing and the goodness of fit of the models.

3.2. Overview of Research Approach

3.2.1. Quantitative approach and qualitative approach

There are two general approaches to comparing the MSPs: quantitative approach and qualitative approach. The qualitative approach focuses on understanding a particular phenomenon and analysing or interpreting the meaningful factors that are not easy to quantify in a deep and comprehensive manner (Ben-Eliyahu, 2014). In many cases, a qualitative approach is used as a complement to a quantitative approach to more clearly understand people's perception, attitude and behaviour. The qualitative approach includes in-depth interviews, triads, brainstorming, paired interviews, accompanied interviews, participation observation, open-ended questions or focus groups (Grosvenor, 2000).

Qualitative approach fosters and encourages creativity in research design. It has the exploratory nature and design flexibility suitable for dealing with a new situation or question. This approach can have a high level of realism with depth and breadth. However, in many cases, a small number of people tend to participate in the research since much time and many resources are needed. Thus, the qualitative approach tends to be limited due to its small sample size. As a result, this approach has limitations of generalizing to the whole population and presenting a broad range of perspectives. To provide concrete evidence, quantitative methods are often required (see **Table 3-1**).

The quantitative approach focuses on approximating phenomenon from some people by using survey methods and applying statistical techniques to recognize overall patterns. It is relatively easy to survey people through scientific and objective methods rather than being inferred subjectively through sensation, reflection, or intuition. This approach tends to provide an accurate measurement of people's behaviour. Since people's responses can be converted to numbers and quantitatively analysed, it tends to apply various statistical techniques or mathematical operations. Thus, more clear results can be obtained, and result generalization is relatively easy.

Table 3-1. Comparison of qualitative approach and quantitative approach

Qualitative approach	
Advantage	Disadvantage
• Allows identification of new phenomenon • Offers a deeper and broader understanding • Provides an informal and anecdotal information • Gives open-ended, dynamic, flexible data	• Has difficulty in generalizing to the general population • Challenges in applying statistical methods • Has difficulty in evaluating relationships between variables • Requires highly executive's skills or orientation • Output is soft data rather than hard data • Be unable to survey repetition
Quantitative approach	
Advantage	Disadvantage
• Collects information from a large number of respondent • Offers statistical and numerical measurement, allowing for comparison • Provides rigorous, reliable, and verifiable aggregates of data • Allows identifying significant relationships between variables by using statistical techniques • Allows survey repetition and comparison of survey results • Less dependent on research executive skills or orientation • Allows generalizing to broader population	• Has difficulty in recognizing new phenomenon • Caution in interpretation without a control group

* Source: Adopted from Berg, 2007; Grosvenor, 2000; Ben-Eliyahu, 2014.

This research can be evaluated with the two methods. In many cases, the quantitative and qualitative approach are ultimately complementary, rather than substitutes. However, considering the objective of this research for investigating the most effective MSP, the quantitative approach is more appropriate for this research than the qualitative approach.

3.2.2. Aggregate approach and disaggregate approach

The demand modelling approach can be classified into the aggregate approach and disaggregate approach. The aggregate approach is a macro level modelling approach representing the behaviour of an entire population or market segment whereas the disaggregate approach is a micro level modelling approach based on individual behaviours. The aggregate approach assumes that average people in the travel demand is homogeneous and have the same travel preference regardless of their characteristics to simplify the model. This approach can offer a tool of the complete modelling process. In contrast, the disaggregate approach presumes that that travellers are heterogeneous and divided into several homogeneous segments. In general, the disaggregate models can more accurately depict the travel decisions made by individuals (Tavasszy and Bliemer, 2013).

The aggregation over unobservable factors gives rise to a probabilistic decision model and the aggregation over the distribution of observable factors leads to the conventional aggregate or macro relations (Ortúzar and Willumsen, 2011). An aggregate approach is a mathematical approach that can quantify travel and forecast accurately under the homogeneity condition (Sivakuma, 2007).

The disaggregate approach is based on surveys of individuals or observations of individual’s real or stated choices. This approach tends to use individual data and apply modelling methodologies such as constrained optimization and random utility maximisation (Tavasszy and Bliemer, 2013). This method views individuals or households as the decision-making unit (Sivakuma, 2007). It is easier to implement and calibrate, more flexible and practical for testing new hypotheses, and more suitable for detailed analyses. It takes into account attributes and socio-economic characteristics of individuals. In general, the disaggregate approach can be considered two kinds of the survey: RP survey and SP survey.

3.2.3. Stated preference approach and revealed preference approach

To assess the effectiveness of various MSPs for modal shift, two approaches can be considered: a simulation-based approach and a survey-based approach. A simulation-based approach is a modelling approach that puts together some explanatory variables necessary for a theoretical framework, and then assesses the influence and variation of the variables through the simulation (Lee, 2011). On the other hand, the survey-based approach aims to assess how much the influence of variables will be on the basis of the survey responses (Lee, 2011). In this study, to assess new MSPs that do not exist yet in South Korea, the survey-based approach would be more appropriate than the simulation-based approach. RP data are data about actual or observed choices made by individuals or households (Fowkes and Wardman, 1988). However, RP data have limitations as follows: (1)

Observations of actual choices may not supply sufficient variability for developing models. (2) Observation may be dominated by a few factors making it difficult to detect the relative importance of other variables. In many cases, the strong correlations between the explanatory variables often exist. (3) RP method cannot be utilized in a direct way to evaluate demand under conditions which do not yet exist. In particular, there are difficulties in collecting responses for entirely new policies. Where data from a real transport market are not available for eliciting reliable preference functions or predicting transport demand, SP method can be an appropriate substitute. That is, SP methods have to be used in situations where suitable RP data do not exit (Preston, 1991; Dissanayake and Morikawa, 2010).

Table 3-2. Advantages and disadvantages of SP approach

Advantages	Disadvantages
▪ Statistical efficiency - can eliminate multicollinearity - can introduce variation - can avoid measurement error - can encourage trading ▪ Data efficiency - can have several observations per individual ▪ Choice context efficiency - can examine new policy instruments - can consider 'softer' factors ▪ Modelling efficiency - can calibrate separate models for each individual. - can investigate alternative functional forms for the utility expression.	▪ Biases - Random bias (non-commitment bias, instrument bias) - Systematic bias (policy response bias, presentation bias) ▪ Respondent fatigue ▪ The scale factor problem - SP can be used for relative values but should be rescaled with RP for absolute forecasts. ▪ The repeat observation problem - The standard error could be deflated by as much as the square root of the number of scenarios as observations is not independent.

* Source: Preston, 2012b.

SP methods refer to a family of techniques that use respondent's statements about their preferences in a set of options to estimate utility functions (Kroes and Sheldon, 1988). SP methods require a purpose-designed survey that leads individuals to express their preferences for the collection of data (Polak and Jones, 1997; Kim, 2001). Therefore, people will be asked to make a choice as to how they would act under hypothetical choice scenarios. Stated responses obtained from the survey can be interpreted as stated behavioural intentions.

SP methods have not only many advantages but also many disadvantages (see **Table 3-2**). Therefore, careful application and sufficient preparation are needed to adopt it successfully. Also, since RP and SP approach should not be thought of as mutually exclusive, it may be reasonable in some situations to combine the two approaches (Preston, 1990).

3.3. Selection of Attributes and Attribute's Level

3.3.1. Determination of alternative-specific and explanatory variables

The most important major factors affecting the choice of travel mode (car and PT) are determined to be the three MSPs as alternative-specific variables. In this study, the basic assumption is that the choice of travel mode is mainly decided by level of transport policy, and level of transport policy depends primarily on travel cost. In these premises, to answer the question of what the most effective MSP in South Korea is, commuter's mode choice under hypothetical choice scenarios should be collected. In responses to the change of level of three hypothetical MSPs, the change of commuter's mode choice is measured. That is, respondents were asked to choose one of the two options based on their preference to various hypothetical choice scenarios.

On the other hand, another purpose of the thesis is to understand what factors affect the choice of travel mode. For this purpose, it is important to appropriately decide what possible explanatory variables are because there are numerous factors affecting commuter's mode choice behaviour. In this study, the key factors that affect the choice of travel mode can be classified as socio-demographic characteristics (e.g. gender, age, and income level), travel characteristics (e.g. travel distance, time and cost), and attitudinal characteristics (e.g. consciousness of congestion severity) (Ortúzar and Willumsen, 2011). The data of these characteristics are collected from the survey questionnaires as possible explanatory variables (RP or SP data). By analysing data about possible explanatory variables, the question can be answered: Why do commuters choose a particular travel mode and what factors influence modal choice patterns in South Korea?

The survey questionnaire consists of five sections, 11 subsections and 107 questions (see **Table 3-3**). The first section (8 questions) is relevant to a respondent's commuting journey. The second section (34 questions) is aimed at evaluating the sensitivity to the three MSPs and understanding how attitudinal factors affect the modal shift effect of the MSP. Through the SP choice survey (27 questions), the commuter's responses to some hypothetical scenarios are obtained. In addition, seven questions with five-point Likert scales are asked to achieve the information on attitudinal factors. The third section (38 questions) covers travel characteristics such as travel time and travel cost. The fourth section (18 questions) aims to collect information on the current situation of parking in the workplace, current conditions about commuting subsidization from the respondent's company, and the opinions on congestion charging. In the fifth section, nine questions that are related to demographic characteristics such as gender, age, and income are represented. The questionnaire of the on-line survey is attached to **Appendix 1**.

Table 3-3. Main content and purpose of questionnaire

Survey field	Purpose	Content of questionnaire	Type
Section A: Factual questions about the respondent and household	To understand the respondent's commuting journey	The location of home, the location of office, the distance from home to work, main commuting transport mode, the frequency of the main transport mode use, the type of vehicle, the main use of private car, number of car which respondent's household has	Open-ended question (3) or closed-ended question (5)
Section B (1): Preference Survey	To evaluate the sensitivity to the three modal shift policies	27 choice questions (a respondent is asked to choice either car or PT under the 27 hypothetical choice scenarios made up of three levels of three modal shift policies)	Binary choice question: car or PT (27)
Section B (2): Questions about individual perception and attitude	To understand how attitudinal factors affect the modal shift effect of MSP significantly	Awareness of congestion severity, environmental awareness about the use of public transport, consciousness between the use of public transport and health, acceptance about governmental regulation to choose a travel mode, the importance of convenience, the importance of commuting time, the importance of commuting cost	Closed-ended question (7) with five-point Likert scales
Section C (1): Questions about the use of private car	To understand the car user's commute journey	Travel time and travel cost when using private car (total travel time, departure time, arrival time, parking time, total commuting cost), car sharing (number of sharing people, etc.)	Open-ended question (10) or closed-ended question (3)
Section C (2): Questions about the use of public transport	To understand the respondent's commute journey	Travel time and travel cost when using public transport (total travel time, departure time, waiting time, arrival time, total commuting cost), transfer (number of transfer, transfer time)	Open-ended question (15) or closed-ended question (7)
Section C (3): Questions about the reason of a travel mode	To understand the reason for using a commute mode	The reason for using a car, the reason for using public transport, the priority to improve the public transport	Multiple closed-ended question (3)
Section D (1): Questions about parking	To understand the current condition of parking	The type of parking lot, the way of paying for parking fee, whether the respondent receives any subsidy or support from company, average parking fee, an amount of parking fee support from company a month	Open-ended question (2) or closed-ended question (3)
Section D (2): Questions about commuting subsidization	To understand the current condition of commuting subsidization	Whether respondent's company gives a commuting grant, the way of receiving commuting grants from company by month, average commuting cost a month	Open-ended question (3) or closed-ended question (2)
Section D (3): Questions about congestion charge	To understand the respondent's opinion about congestion charge	the most appropriate cordon in Seoul, the appropriate level of charge per day, the appropriate application time, the value of 10 minutes reduced time, traffic delay time	Open-ended question (2) or closed-ended question (3)
Section D (4): Questions about modal shift policy	To understand the respondent's opinion about modal shift policy	The most effective and acceptable MSP in the short term and the long term, the type of commute mode when it is impossible to use respondent's car	Multiple closed-ended question (3)
Section E: Factual questions about the respondent and household	To understand the respondent's demographic condition	Gender, age, income, education career, occupational sector, physical disability, household size, whether the respondent has a child or children, the number of workers in his/her household	Closed-ended question (9)

* Parenthesis ( ): number of question

3.3.2. Determination of attribute levels

In this study, the attributes are associated with economic incentive or disincentive MSPs in urban transport. The focus is placed on the economic fundamentals of urban transport policies. Although travel time and modal reliability are known to have a significant role, the economic policy in urban transport may be the most likely and practical policy.

Travel time is always used to be considered as a disutility in the transportation. TDM involving the reduction of travel time such as the improvement of transport services or EMBL can be the main subject of study. However, the improvement of transport services takes a long time and much budget and has a relatively indirect impact. In addition, Jaensirisak et al. (2001) indicated that car and bus delayed-time reductions did not show a significant effect. Although there are, generally, effects of enhancement of convenience, the impact of improvement does not guarantee the change of selection of travel mode. Additionally, there are many EMBLs in trunk roads in Seoul. Therefore, there are limitations in the new introduction of EMBL due to physical limitations such as narrowed roads. First and foremost, the characteristics of policy related to the reduction of travel time seem to be closer to a supply side policy than a demand-side policy. Therefore, there are limitations of using the main subject in this study because MSP seems to focus on the demand side policy in terms of the characteristics of policy. Meanwhile, in many cases, travel time is frequently changed into the monetary unit because the monetary value can be derived from travel time. Therefore, in the survey, the implementation of congestion charging is assumed to gain a certain percentage of the reduction of travel time (see **Table 3-4**).

Table 3-4. Level of alternative-specific attribute (basic criterion: commuting cost per day)

Type of policy	Attributes of variables	Level of attributes
PT commuting cost subsidy	Subsidy rate of PT cost from company (measurement: %)	(0) 1 level 0% (1) 2 level 50% (2) 3 level 100%
Parking price	Increase of parking fee at workplace per day (measurement: won = ₩)	(0) 1 level ₩0 [Suppose £1 = ₩1,800 (KRW, won)] (1) 2 level ₩2,500 (£ 1.39) (2) 3 level ₩5,000 (£ 2.78)
Congestion Charging	Amount of congestion charge per day (measurement: won = ₩)	(0) 1 level ₩0 (1) 2 level ₩3,000 (£ 1.67)(10% reduction of total travel time) (2) 3 level ₩6,000 (£ 3.3)(20% reduction of total travel time)

This survey introduces the three cost-pricing policies since the increase of travel cost for traveller would be most effective (Meyer, 1999). Congestion charging and PT commuting cost subsidy have not yet been implemented in South Korea, and parking pricing has not been raised as an MSP. The experimental design of the MSP includes both ‘carrot’ and ‘stick’ strategies.

The SP experiment simulated the binary choices between PT and car by offering commuter 27 comparisons. In each comparison, permissible responses are on two modes. The difference between the two modes may be characterised by the hypothetical levels of three attributes. The attributes and attribute levels in the design are specified to cover the range of possibilities allowing estimation of possible non-linear effects for quantitative attributes (Brownstone et al., 2000).

The values of each attribute level were determined to be approximately the same economic level (Lee et al., 2005). Each attribute has three levels to identify the sensitivity of each policy corresponding to the change of the economic value or price.

Meanwhile, congestion charging has the enormous effect of travel time reduction, considering London or Singapore case. In the case of London, congestion was reduced to about 25% and traffic levels by 20% in the first two years after the implementation of congestion charging (£5 in 2003, £8 in 2005, £9 ~ £11 in 2011). For 2003 ~ 2005, average car speeds within the zone had increased 37%, and peak period delays had decreased 30%. In Singapore, the establishment of the restricted zone (purchase price of entering licence: US $ 2.20 daily) led to a reduction of 31% of traffic in the area. Through electronic road pricing, the morning peak hour traffic was reduced by 7 ~ 8% (Strompen et al., 2012). Therefore, the consideration of the travel time reduction effect may be needed in the survey composition. In contrast, in South Korea, the increase of parking price plays a role in just a tool of the financial burden, not a tool of travel time reduction. Many Koreans think that the increase in parking price has little effect on travel time reduction. This is partly because the consistent parking price policy in the wide area has not been implemented in South Korea.

Table 3-5. Fare level of PT in the metropolitan Seoul city

<table>
<tr><th>Classification</th><th>Type</th><th>Transport card</th><th>Cash</th><th>Note</th></tr>
<tr><td rowspan="2">Subway</td><td>Adult</td><td>₩1,050 (= £0.58)</td><td>₩1,150 (= £0.64)</td><td rowspan="8">* Singular subway:
- Within 10 km: ₩1,050
- 10 ~ 40km: add ₩100 per 5km
- Over 40km: add ₩100 per 40km
* Singular bus: basic fare
* Integrated distance scale rates fare system
- Regardless transfer number (up to 5 times) ₩ 1,050 within 10km, after then ₩100 per 5km
- Transfer available time: within 30 minutes after stopover</td></tr>
<tr><td>Disabled</td><td colspan="2">Free</td></tr>
<tr><td rowspan="2">Line bus</td><td>Adult</td><td>₩1,050 (= £0.58)</td><td>₩1,150 (= £0.58)</td></tr>
<tr><td>Disabled</td><td colspan="2">Free</td></tr>
<tr><td rowspan="2">Town bus</td><td>Adult</td><td>₩ 750 (= £0.42)</td><td>₩ 850 (= £0.47)</td></tr>
<tr><td>Disabled</td><td colspan="2">Normal fare</td></tr>
<tr><td rowspan="2">Circular bus</td><td>Adult</td><td>₩ 850 (= £0.47)</td><td>₩ 950(= £0.53)</td></tr>
<tr><td>Disabled</td><td colspan="2">Free</td></tr>
<tr><td rowspan="2">Regional bus</td><td>Adult</td><td>₩1,850 (= £1.03)</td><td>₩1,950 (= £1.08)</td><td rowspan="4">* Transfer fare: add ₩100 per 5km when using more than 30km</td></tr>
<tr><td>Disabled</td><td colspan="2">Normal fare</td></tr>
<tr><td rowspan="2">Regional express bus</td><td>Adult</td><td>₩2,150 (= £1.19)</td><td>₩2,250 (= £1.25)</td></tr>
<tr><td>Disabled</td><td colspan="2">Normal fare</td></tr>
</table>

* In **Table 3-5**, there are no remarkable differences between regular bus fare and subway fare in Seoul. In addition, the transfer discounts are applied to both. Therefore, the distinction between bus and subway almost disappears at the moment in aspect of the finance.

Table 3-6. Fare level of taxi in the metropolitan Seoul city

Classification	Basic fee	Driving fee	Time fee	Late-night charge	Outside area charge
Medium sized taxi	2km ₩2,400 (£ 1.33)	₩100 (£ 0.06) per 144 m	₩100 (£ 0.06) per 35 seconds	20% (extra charge)	20%
Large sized taxi	3km ₩4,500 (£ 2.5)	₩200 (£ 0.11) per 164 m	₩200 (£ 0.11) per 39 seconds		
Small sized taxi	2km ₩2,100 (£ 1.17)	₩100 (£ 0.06) per 155 m	₩100 (£ 0.06) per 37 seconds	20%	20%

* For example: when using the medium sized car, taxi fare of 5 km driving is about ₩4,500 (£ 2.5), and that of 10 km driving is about ₩8,000 (£ 4.44).

* In South Korea, taxi sometimes used to be classified as a kind of PT because taxi fare is very cheap. Especially, the use of taxi in the inconvenient PT area or short move with taxi from home to the station or from station to office is a common practice in South Korea.

In setting up too wide a range of attribute levels, a biased choice may be result in dominated alternatives (Hess and Rose, 2009). Additionally, too narrow a range of attribute levels may bring about a confused choice for which the respondent will have trouble in distinguishing between them. Therefore, the level of each attribute should be decided carefully. When it comes to the commuting cost, regular bus fare is 1,150 won (£0.63) for an adult, town bus fare is 850 won (£0.47), metropolitan area bus fare is 1,950 won (£1.07) and subway fare is 1,150 won (£0.63) within 10km (see **Table 3-5**). Basic taxi fare within 2km is 2,400 won (£1.33) (see **Table 3-6**). Hence, the average commuting fare of PT users per day can be assumed to be about 2,100 ~ 6,000 won [the survey result gives an average 4,422 won (£2.46)]. As for congestion charging, if the average commuting time for car users is about 50 minutes in Seoul (in this survey, average total commuting time of car users from home to work is 46 minutes 24 seconds), the value of a reduction of travel time of between 5 and 10 minutes) can be considered between 500 to 1,000 won [the survey result: average 661 won (£0.37) when considering 10% of total travel time]. For reference, the basic unit, such as the level of attributes, is based on a daily trip to readily assess the modal shift effect of MSP. All in all, the intervals of the attribute levels can be considered acceptable. The amount of policy intervention under the maximum hypothetical scenario (15,422 won, £8.57) is also acceptable since Gangnam is one of the wealthiest areas in South Korea. Therefore, it is expected that many car users in Gangnam area may endure its economic burdens.

In this survey, the purpose of the experimental design is to investigate the modal shift effects of MSPs associated with the two alternatives: car or PT. Therefore, respondents were asked to choose one of two alternatives. In terms of the reduction of car use, the separation of PT such as buses, subways, trains is not needed. In many cases, many commuters who mainly use PT are accustomed to using indistinctly various PTs or both because the majority of Seoul areas provide various PTs and transfer discount. Thus, to investigate the most effective MSP, the division of PT is not of importance. In particular, since a full factorial design (27) in this study can cause confusion of respondent’s choice, the simplicity of choice mechanism is required rather than other surveys.

3.4. A Full Factorial Design

The experimental design can be implemented by an orthogonal method. To compare the preference of alternative policies, an orthogonal array table can be utilized. According to Kocur et al. (1982), an orthogonal design means that those effects and interactions, which are estimable in a given design, can be estimated without correlation with other main effects or with those interactions, which are not assumed negligible. Through the orthogonality of an experimental design, the attributes of the experiment can sustain their statistical independence (Rose and Bliemer, 2009). **Table 3-7** shows the advantages and disadvantages of a full factorial design. A full factorial design can be orthogonal in terms of the main effects of designs and all interaction effects. That is, a full factorial design can be estimated without correlation with main effects and interaction. A full factorial design can include all possible combinations of attribute levels (Albert and Mahalel, 2006). If all interactions are of interest, a full factorial design is needed (Sanko, 2001; Pearmain and Kroes, 1990). On the other hand, a fractional factorial design has an advantage in terms of the smaller number of scenarios required from each individual, but it is more difficult to analyse and interpret data deeply.

Table 3-7. Advantages and disadvantages of a full factorial design

Advantages	Disadvantages
▪ All possible combination of attribute levels can be used (unrestricted test design) ▪ All main effects and interaction effects can be estimated ▪ All main effect can be more accurately estimated ▪ No correlations between attribute levels	▪ Too many questions for a single respondent (respondent fatigue, measurement error) ▪ Trivial choice situation can be contained (many missing data and fallacies can be made)

* Source: Adapted from Rose and Bliemer, 2006; Sanko, 2001; www.clickz.com, 2011

As shown in **Table 3-8**, the design index is a listing and description of the experimental plans. The master plan gives the specific combinations of variables for each experimental trial for the plans listed in the design index (Kocur et al., 1982). Thus, the master plan is located from the description in the design index. This experimental design has three variables, and each variable has three levels each. The number of tests required is 27 (see Column 4). This test plan code corresponds to 16b (see Column 1) and can apply the Master Plan Number 8 (see Column 8). Plan 16b allows the estimation of all interactions. If we assign variables to Master Plan Columns 1, 2, and 5, respectively (see Column 9 in **Table 3-8** and **Table 3-9**), Plan 16b allows the estimation of all two-factor interactions (see Column 10). An array of preference questions can be created by the Kocur's Table.

Table 3-8. Design index (Kocur et al., 1982)

1	2	3b	4	5	6	8	9	10
Depart-ment Plan Code No.	Total No. of Variables	No. of Variables at 3 Levels	No. of Tests Required	Are all Main Effects Independent of 2-Factor Interactions?	No. of Independent 2-Factor Interactions under Assumed Model	Master Plan No.	Using Columns No.	Columns from which 2-Factor Interactions can be estimated
16b	3	3	27	Yes	3 (All)	8 (FF)	1, 2, 5	All

* Department Plan Code Number: This column identifies a specific plan.
* Master Plan Number: This column indicates the plan in the master list from which to select the exact treatment combinations. The notation “FF” denotes full factorial design. These designs can be constructed by taking all possible combinations of levels for each of the variables.
* Using Columns Number: This column specifies the exact column to choose from the master plan indicated in Column “Master Plan Number” (see Column 8 and the first Column in **Table 3-9**).
* Number of Independent Two-Factor Interaction under Assumed Model: This column indicates the number of two-factor interactions that can be estimated independently of main effects and other estimable two-factor interactions.

Table 3-9. Master plan 8: 27 trials

00000 12345	00001 67890	111 123	11111 45678	12222 90123	222 456
00000	00000	000	00000	00000	000
00001	12121	212	00001	10101	010
00002	21212	121	00000	01010	101
01120	00111	122	01100	00111	100
01121	12202	001	01101	10000	001
01122	21020	210	01100	01000	010
02210	00222	211	00010	00000	011
02211	12010	120	00011	10010	100
02212	21101	002	00010	01101	000
10110	11001	111	10110	11001	111
10111	20122	020	10111	00100	000
10112	02210	202	10110	00010	000
11200	11112	200	11000	11110	000
11201	20200	112	11001	00000	110
11202	02021	021	11000	00001	001
12020	11220	022	10000	11000	000
12021	20011	201	10001	00011	001
12022	02102	110	10000	00100	110
20220	22002	222	00000	00000	000
20221	01120	101	00001	01100	101
20222	10211	010	00000	10011	010
21010	22110	011	01010	00110	011
21011	01201	220	01011	01001	000
21012	10022	102	01010	10000	100
22100	22221	100	00100	00001	100
22101	01012	012	00101	01010	010
22102	10100	221	00100	10100	001

* Source: Kocur et al., 1982.

Table 3-10 shows the twenty-seven hypothetical conditions made up of three levels of three attributes with a full factorial design. This full factorial plan is based on the catalogue of the design index and master plan 8 of Kocur et al. (1982). Each attribute that has respectively three levels (3^3) is uncorrelated in regard to each other (Chrzan and Orme, 2000). As a result, a full factorial design allows to estimate all eight coefficients associating with the main effect and interaction effect of MSP.

Table 3-10. Adoption of MSPs with full factorial design

Classification	PT subsidy	Parking fee	Congestion charge
Condition 1	0 % (level 0)	0 won (level 0)	0 won (level 0)
Condition 2	0 % (level 0)	0 won (level 0)	3,000 won (10% reduction of total travel time) (level 1)
Condition 3	0 % (level 0)	0 won (level 0)	6,000 won (20% reduction of total travel time) (level 2)
Condition 4	0 % (level 0)	2,500 won (level 1)	0 won (level 0)
Condition 5	0 % (level 0)	2,500 won (level 1)	3,000 won (10% reduction of total travel time) (level 1)
Condition 6	0 % (level 0)	2,500 won (level 1)	6,000 won (20% reduction of total travel time) (level 2)
Condition 7	0 % (level 0)	5,000 won (level 2)	0 won (level 0)
Condition 8	0 % (level 0)	5,000 won (level 2)	3,000 won (10% reduction of total travel time) (level 1)
Condition 9	0 % (level 0)	5,000 won (level 2)	6,000 won (20% reduction of total travel time) (level 2)
Condition 10	50 % (level 1)	0 won (level 0)	0 won (level 0)
Condition 11	50 % (level 1)	0 won (level 0)	3,000 won (10% reduction of total travel time) (level 1)
Condition 12	50 % (level 1)	0 won (level 0)	6,000 won (20% reduction of total travel time) (level 2)
Condition 13	50 % (level 1)	2,500 won (level 1)	0 won (level 0)
Condition 14	50 % (level 1)	2,500 won (level 1)	3,000 won (10% reduction of total travel time) (level 1)
Condition 15	50 % (level 1)	2,500 won (level 1)	6,000 won (20% reduction of total travel time) (level 2)
Condition 16	50 % (level 1)	5,000 won (level 2)	0 won (level 0)
Condition 17	50 % (level 1)	5,000 won (level 2)	3,000 won (10% reduction of total travel time) (level 1)
Condition 18	50 % (level 1)	5,000 won (level 2)	6,000 won (20% reduction of total travel time) (level 2)
Condition 19	100 % (level 2)	0 won (level 0)	0 won (level 0)
Condition 20	100 % (level 2)	0 won (level 0)	3,000 won (10% reduction of total travel time) (level 1)
Condition 21	100 % (level 2)	0 won (level 0)	6,000 won (20% reduction of total travel time) (level 2)
Condition 22	100 % (level 2)	2,500 won (level 1)	0 won (level 0)
Condition 23	100 % (level 2)	2,500 won (level 1)	3,000 won (10% reduction of total travel time) (level 1)
Condition 24	100 % (level 2)	2,500 won (level 1)	6,000 won (20% reduction of total travel time) (level 2)
Condition 25	100 % (level 2)	5,000 won (level 2)	0 won (level 0)
Condition 26	100 % (level 2)	5,000 won (level 2)	3,000 won (10% reduction of total travel time) (level 1)
Condition 27	100 % (level 2)	5,000 won (level 2)	6,000 won (20% reduction of total travel time) (level 2)

Figure 3-1. Composition of questionnaire

Condition:	when you use public transportation	when you use a car
(15)	□ Public transport commuting cost subsidy: 50%	□ Parking fee: add 2,500 won more than present level per day □ Congestion charging: levy 6,000 won per day (20% reduction of total travel time)

Choice: ☐ **Public Transport Use** ☐ **Car Use**

Figure 3-1 shows an example of the composition of the questionnaire. Respondents were asked to choose either car or PT. Their answers provide information as to what extent the MSP would be more effective in reducing car usage.

3.5. Survey Area

The survey was carried out in Seoul City, in South Korea through an online survey. Seoul city has been chosen as the study locality because it has high car ownership and car use and various PTs available. In South Korea, Seoul City has been suffering from severe traffic congestion and is confronted with the pressure to improve the situation from the public because a third of the population of South Korea live in Seoul metropolitan area. **Table 3-11** compares London area and Seoul area. Due to the high density of population in narrowed region, the traffic congestion and environmental problems are emerged as major social issues in Seoul.

Table 3-11. Comparison of Seoul area and London area (2007)

Classification		Greater London (GE)	Seoul
Area		**1,572km^2** (0.65%)	**605km^2** (0.61%)
Population		**7,500,000** (12.59%)	**10,300,000** (21.90%)
Road length (m)		14,415,000	8,067,201
Number of cars		**2,856,857**	**2,582,000**
Road length per capita (m)		5.63	2.82
Number of cars per capita		0.34	0.29
Subway (2006 data)	Coverage (km)	408.0	296.9
	Number of lines	12	8
	Number of stations	275	263
	Number of users	**978,000,000**	**2,268,406,000**
Bus (2006 data)	Coverage (km)	6,653.0	9,472.5
	Number of lines	700	395
	Number of stations	17,5000	7,766
	Number of users	1,800,000,000	1,689,250,000
Market share of transport mode	Car (%)	40	19
	Transit (%)	29	58
	Others (%)	31	23

- London metropolitan (GE + South East Region): area 20,641km^2(8.47%), population 15,750,000 (26.4%)
- Seoul metropolitan: area 11,782km^2 (11.82%), population 23,750,000 (50.55%)
* Source: Transportation for London, focus on London 2007, Office of National Statistics, and Seoul annual statistics 2007.

In Seoul, the Gangnam area (see **Figure 3-2**) was selected for the survey location as this is one of the most congested areas as well as being a well-developed area in the county. This area has a wide range of businesses such as IT, construction, real estate and financial companies. In addition, there are a lot of commuters to clearly express their preference. **Table 3-12** shows the present condition of employed workers in the Gangnam area. There are a wide range of commuters in diverse fields of work because Gangnam is considered as a new CBD in Seoul and the largest business area in South Korea. In addition, Gangnam is the most likely area to introduce congestion charging in South Korea because it is one of the most heavily congested ones. However, diverse and well-equipped PTs are relatively sufficiently provided. Therefore, clear results can be expected when doing research.

Figure 3-2. Map of Gangnam area (Gangnam-Gu and Seocho-Gu)

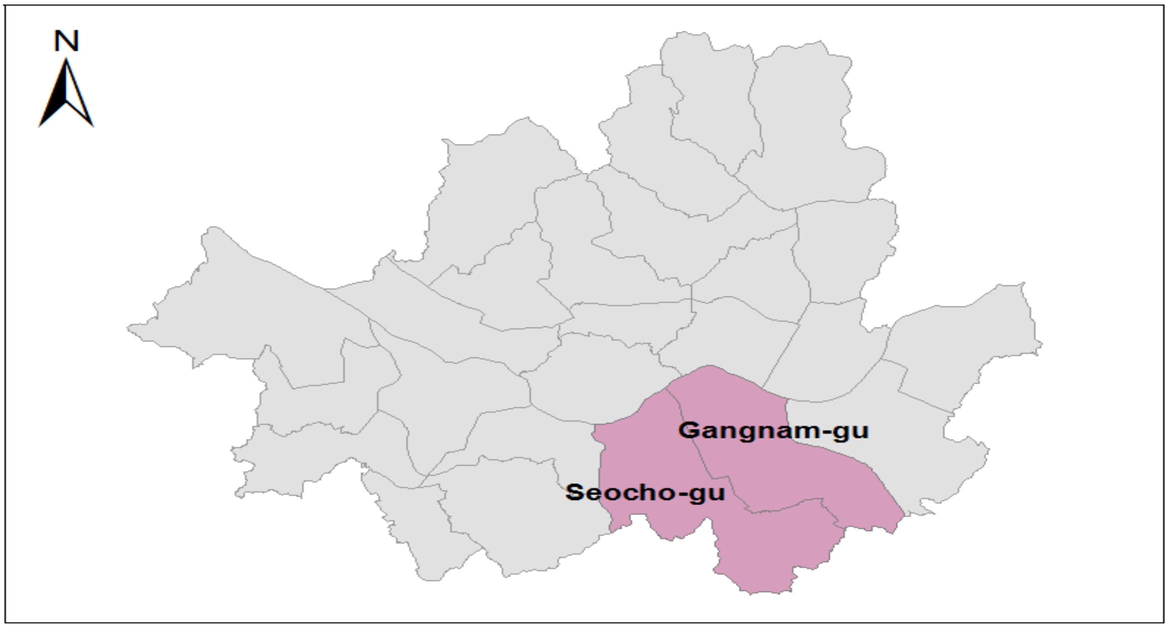


Table 3-12. Workers in the Gangnam-Gu and Seocho-Gu

Classification (2011)	Establishments	Number of worker		
		Sum	Male	Female
Seocho-Gu	42,602 (40.55%)	376,962 (38.15%)	237,187 (39.61%)	139,775 (35.90%)
Gangnam-Gu	62,448 (59.45%)	611,206 (61.85%)	361,607 (60.39%)	249,599 (64.10%)
Total	105,050 (100%)	988,168 (100%)	598,794 (60.60%)	389,374 (39.40%)

* Source: National statistics office data of South Korea, 2012.

3.6. Determination of Sample Size

One way of reducing sampling error is to increase sample size. However, the question remains as to how much researchers should increase the sample size to obtain an acceptable degree of sampling error. While too large samples will be too costly, too small samples can lead to a large degree of variability and poor reliability. Therefore, the most effective sample size should be located somewhere between the two extremes. In many cases, Cochran's sample size (*n*) formula (1977) for categorical data can be used as follows (Bartlett et al., 2001):

$$n = \frac{(\underline{t})^2 * (p)(q)}{(\underline{d})^2}$$

where $\underline{t}$ = value for selected alpha level[4] of 0.025 in each tail = 1.96 (the alpha level of 0.05), (p)(q) = estimate of variance = 0.25 (in case of the application of standard deviation of the scale as 0.5), d

[4] Alpha (α) level is the probability of rejecting the null hypothesis when the null hypothesis is true (Sandra, 2007). The lower the alpha, the more stringent the test. The lower the alpha, the larger the sample size.

= acceptable margin of error for proportion being estimated = 0.05 (error the researcher is willing to accept).

The alpha level, the level of risk which the researcher is willing to take that the true margin of error exceeds the acceptable margin of error, is incorporated into the formula by utilizing the t-value for the alpha level selected (e.g. t-value for alpha level of 0.05 is 1.96 for sample size above 120) (Bartlett et al., 2001). In general, an alpha level of 0.05 is acceptable for most research. In addition, for categorical data, 5% margin of error[5] is acceptable.

$$n = \frac{(1.96)^2 * (0.5)(0.5)}{(0.05)^2} = 384$$

In conclusion, through Cochran's sample size formula, which uses the binomial distribution, the minimum sample size can be determined by population size and alpha level. In general, more than 384 samples can be accepted in most research. Therefore, this number applies to this research.

Meanwhile, if the sample size for each segment is large enough to accommodate at least 75~100 numbers of each segment, meaningful results can be obtained (Myers and Tauber, 2011). However, the concentration on specific segments is not necessary since this research regarded the conversion effect of the MSP without regard to specific classifications. In this study, the number of total samples is 776. However, the number of final valid samples for developing models is 767, which means that modal share can be estimated with a margin of error of 0.035386.

<Calculation of margin of error>

$$n_0 = \frac{(\underline{t})^2 * (p)(q)}{(\underline{d})^2} \rightarrow d = t\sqrt{\frac{pq}{n}} \rightarrow \frac{d}{t} = \sqrt{\frac{pq}{n}} \rightarrow \left(\frac{d}{t}\right)^2 = \frac{pq}{n} \rightarrow \frac{d^2}{t^2} = \frac{pq}{n} \rightarrow \frac{d^2}{1.96^2} = \frac{0.5*0.5}{767} \rightarrow d = 0.035386$$

In this study, the number of workers in the Gangnam area with a driving license and an available car cannot be exactly collected. However, as shown in **Table 3-12**, the total population of workers in the Gangnam area was 988,168 as of 2011. The sample of 767 responses out of the population of 988,168 seems to be very small. The sample is just 0.078% of the population. However, except for surveys of the very small population, the bottom line is the number of observations rather than the actual size of the population in terms of accuracy (Arsham, 2009). For instance, a sample of 800 from a population of 1,000,000 is as precise as a sample of 800 from a population of 100,000.

[5] The margin of error is a statistic expressing the amount of random sampling error, which quantifies uncertainty, in a survey's results. In general, the larger the margin of error, the less confidence. In addition, the size of a sample is a crucial factor affecting the margin of error (Scheuren, 2004).

3.7. Modelling Methods

3.7.1. Development of logit models

3.7.1.1. Theoretical Framework

The search for the best model specification involves determining the appropriate functional form. Although the linear function is appropriate in many contexts, the non-linear function is more appropriate for binary choice (Foerster, 1981). Since the dependent variable is a discontinuous categorical variable, not a continuous variable in this study, the linear function cannot sensibly be introduced. Non-linear functions include probit, logit and logistic regression for dichotomous responses. In general, a model for categorical response is the model with the assumption that the response variables follow a binary probability distribution or a Poisson probability distribution. However, the Poisson distribution is a discrete probability distribution that represents the probability of some events occurring randomly in specific disjoint time intervals (Shenoy et al., 2002). Due to the characteristics of the Poisson distribution, this distribution cannot be used in this study. In addition, a probit model that is assumed to have the normal distribution is relatively complex since the parameter cannot be estimated separately from the standard deviation (Ortúzar and Willumsen, 2011). Consequently, the binary logit model is more suitable for this study.

3.7.1.2. Development of logit models

According to Ben-Akiva and Lerman (1985), the choice of the functional form should be satisfied with the two criteria. First, in terms of theoretical criteria, how the various variables affect the utility of decision-makers should be explained. Second, unknown parameters can be easily and efficiently estimated in the calculation. It is assumed that there is a relationship of the linear in the parameters to meet the former requirement. To achieve this objective, the three MSPs affecting the choice of travel mode are determined as alternative-specific variables in the specification of models. The utility function for a choice alternative consists of 'an observed, systematic, and quantifiable part (V)' and 'an unobservable and random part (ε)' in the choice set (Williams, 1981; Hensher, 1997; Dissanayake et al., 2012). The observed and deterministic utility part (V) is composed of utility weights for explanatory variables (e.g. β_1, β_2, and β_3) and the level value of variables (e.g. $Subsidy_j$, $Park_j$, and $Congestion_j$) in the utility function (Kroes and Sheldon, 1988). $V_{i,\,car}$ and $V_{i,\,PT}$ (i.e. the sum of the taste parameters times the corresponding attributes) are linear in the observed variables with parameters as coefficients (Munizaga et al., 2000). The observed and deterministic utility part (V) reflects the representative tastes of the population as a utility indicator of representative tastes

(McFadden, 1973). In addition, the random and stochastic utility part (ε) reflects the idiosyncrasies of the individual in taste for the alternative with attributes (McFadden, 1973; Lee et al., 2005). The utility functions of travel user *i* can be expressed as follows (Train, 2003; Lee et al., 2005):

$$U_{i,\,car} = V_{i,\,car} + \varepsilon_{i,\,car} = \beta_0 + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \varepsilon_{i,\,car} \tag{3-1}$$

$$U_{i,\,PT} = V_{i,\,PT} + \varepsilon_{i,\,PT} = \beta_1 \cdot Subsidy_j + \varepsilon_{i,\,PT} \tag{3-2}$$

- $U_{i,\,car}$: the utility of car as a travel mode for car user *i*
- $U_{i,\,PT}$: the utility of PT as a travel mode for PT user *i*
- $V_{i,\,car}$: observable and deterministic part of the utility of car user *i*
- $V_{i,\,PT}$: observable and deterministic part of the utility of PT user *i*
- $\varepsilon_{i,\,car}$: unobservable and stochastic part of the utility of car user *i*
- $\varepsilon_{i,\,PT}$: unobservable and stochastic part of the utility of PT user *i*
- $Subsidy_j$: the alternative policy *j* to the application of the commuting cost subsidy for PT user
- $Park_j$: the alternative policy *j* to the application of the additional parking fee to car user
- $Congestion_j$: the alternative policy *j* to the application of the congestion charge to car user
- β_1, β_2, β_3: the coefficient or the weight associated with attribute $Subsidy_j$, $Park_j$ or $Congestion_j$
- β_0: Alternative-Specific Constant

In general, Alternative-Specific Constant (ASC) is a coefficient not involved with any of the observed and measured attributes, which represents the role of all the unobserved sources of utility affecting travel mode choice and the average value of the random terms $\varepsilon_{i,\,car}$ or $\varepsilon_{i,\,PT}$ (Ben-Akiva and Bierlaire, 1999). That is, ASC captures the average effect on the utility of all factors that are not included in the model (Train, 2003). β_0 represents characteristics left out of the equation, but it includes whatever is needed to make error terms that are normally and independently distributed. According to Train (1986), "a model estimated with ASC will reproduce the observed shares in the estimation sample". In addition, "The inclusion of ASC can mitigate, and in some cases remove, inaccuracies due to logit's independence of irrelevant alternatives property" (Train, 1986).

On the other hand, by subtracting the utility of PT user *i* from the utility of car user *i*, the integrated utility functions including both car user *i* and PT user *i* are developed as follows:

$$\begin{aligned} U_{i,\,car} - U_{i,\,PT} &= \beta_0 + \beta_2 \cdot PPark_j + \beta_3 \cdot Congestion_j + \varepsilon_{i,\,car} - \beta_1 \cdot Subsidy_j - \varepsilon_{i,\,PT} \\ &= \beta_0 - \beta_1 \cdot Subsidy_j + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \varepsilon_{i,\,car} - \varepsilon_{i,\,PT} \end{aligned} \tag{3-3}$$

In this case, if the utility of PT user *i* ($U_{i,\,PT}$) is zero, the utility of car user *i* is easily obtained as **Equation 3-4**.

$$U_{i,\,car} = \beta_0 - \beta_1 \cdot Subsidy_j + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \varepsilon_{i,\,car} - \varepsilon_{i,\,PT} \quad (3\text{-}4)$$

If the utility of the car is greater than the utility of PT, the respondent *i* will choose a car. Thus, the probability that a respondent *i* chooses a car is given by (Train, 2003):

$$\begin{aligned} P_i\,(car/\{PT,\,car\}) &= \text{Prob}\,(U_{i,\,car} > U_{i,\,PT},\ \text{for all } car \neq PT) \\ &= \text{Prob}\,(V_{i,\,car} + \varepsilon_{i,\,car} > V_{i,\,PT} + \varepsilon_{i,\,PT},\ \text{for all } car \neq PT) \\ &= \text{Prob}\,(V_{i,\,car} - V_{i,\,PT} > \varepsilon_{i,\,car} - \varepsilon_{i,\,PT},\ \text{for all } car \neq PT) \quad (3\text{-}5) \end{aligned}$$

The probability that an individual *i* selects a car ($P_i\,(car/PT,\,car)$) is a function of the difference in utility between car and PT (Wardman, 1988). Although the distribution of random residuals ε is not known, it can be assumed that the random residuals ε are independently identically distributed (IID) with the Weibull (Gumbel, Gnedeko, extreme value) distribution (McFadden, 1973). It means the distribution of random residuals is supposed to be Extreme Value Type I (EV 1). This distribution is that it is closed to maximisation. Thus, ε has zero mean (Train, 1993). This distribution is the most popular in a discrete choice model (Ortúzar and Willumsen, 2011). It is assumed that choices are consistent with the 'Independence from Irrelevant Alternatives' (IIA) property (Hanley et al., 1998). The percentage of choice probabilities of any alternatives is unaffected by the systematic utilities of any other alternatives (Ben-Akiva and Lerman, 1985). This probability rate for the two alternatives depends only on the characteristics of two alternatives and not on those of other alternatives (Croissant, 2012). With this assumption, the conditional logit model is obtained. In addition, the choice probability of car user *i* is given by (Train, 2003; Richardson et al., 1995):

$$P_i(car/PT,\,car) = P^i_{car} = \frac{e^{\lambda V_{i,car}}}{e^{\lambda V_{i,car}} + e^{\lambda V_{i,PT}}} \quad (3\text{-}6)$$

where λ is a scale parameter related inversely to variance σ^2 of random residuals ε (Munizaga et al., 2000). In the case of linear-in-parameters utilities, the parameter λ cannot be distinguished from the overall scale of the β. In other words, since λ cannot be estimated separately from the parameter β, it can be supposed that λ is normalized to one, meaning constant error variance (Ben-Akiva and Lerman, 1985; Ortúzar and Willumsen, 2011). Therefore, the choice probability of car user *i* is (Train, 2003):

$$P_i(car/PT,\,car) = \frac{e^{V_{i,car}}}{e^{V_{i,car}} + e^{V_{i,PT}}} \quad (3\text{-}7)$$

On the other hand, after the denominator and the numerator are divided by $e^{V_{i,car}}$, the probability of car user *i* in **Equation 3-7** can be converted as follows (Train, 2003):

$$P_i(car/PT,\,car) = \frac{1}{1 + [e^{V_{i,PT}} / e^{V_{i,car}}]} \quad (3\text{-}8)$$

If the utility of choosing a PT ($V_{i, PT}$) is zero, the exponential utility [$e^{V_{i,PT}}$] will be one. $V_{i, PT}$ can be fixed at zero in order to calculate the probability of car user *i*.

$$P_i\,(car/PT,\,car) = \frac{1}{1 + \{\frac{1}{e^{V_{i,car}}}\}} \tag{3-9}$$

Meanwhile, since the sum of the probability of choosing all alternatives is one, the probability of PT user *i* can be obtained by subtracting the probability of car user *i* from one. Thus, if the choice probability of car user *i* is estimated, the choice probability of PT user *i* can be easily obtained. The choice probability of PT user *i* is given by:

$$P_i\,(PT/PT,\,car) = 1 - P_i\,(car/PT,\,car) \tag{3-10}$$

In the logit model, the relative superiority of car and PT depends on the only specific characteristics of two alternatives and is not related to the specific characteristics of other alternatives. In general, a logit model has the characteristics like below (Train, 1986). First, the probability of choosing alternatives *k* has the particular value ranged from zero to one. If some respondents do not have any attraction of alternatives *k*, the deterministic utility of alternatives *k* will access to minus infinity and $P_i(k)$ will access to zero. Second, the sum of the choice probability of each alternative becomes one as long as all the alternatives are summed. This means that the alternative selected is mutually exclusive and a decision maker should choose the only one alternative out of possible choice sets. Third, the relationship between the choice probability and the deterministic utility has a S shaped curve (Train, 1986).

3.7.1.3. Application of utility theory and the method of maximum likelihood

The logit models are ultimately based on the theory of utility maximisation (Ben-Akiva and Lerman, 1985). The underlying assumption is that every decision-maker chooses the most desirable and attractive alternative out of all the alternatives. That is, an individual selects a travel mode that gives maximum utility after comparing the utilities of an available choice set of alternatives. In the theory of the utility, every individual tries to get the maximum utility. The respondent's binary response (0: PT use, 1: car use) is the result of utility maximization under the hypothetical scenarios. Each of answer is the maximum utility of the respondent. The selection of one alternative over another means that the utility of one travel mode (i.e. $U_{i, car}$) is greater than the utility of another travel mode (i.e. $U_{i, PT}$). The *i*-th respondent (*i* = 1, 2, 3, 4, ‥‥, *N*) facing the SP questionnaires of policy alternatives *j* (*j* = 1, 2, 3, 4, ‥‥, M) should determine 'car' or 'PT'. In this case, log-likelihood function can be expressed as follows (Train, 2003):

$$\text{In } L = \sum_{i=1}^{N} \sum_{j=1}^{M} \{Y_{i,j} \cdot \ln[P_{i,j}(k/C)]\} \tag{3-11}$$

where if $Y_{i,j}$ equals one (1), which is an indicator function. If the *i*-th respondent chooses a travel mode k under the alternative policy j, it will be one. Otherwise, it will be zero. Log-likelihood function can be estimated by using Maximum Likelihood Estimation (MLE).

In general, two model estimation techniques have been used for developing the discrete choice models in order to estimate the value of the unknown coefficients, namely the method of Maximum Likelihood (ML) and Ordinary Least Squares (OLS). The method of OLS or linear least squares is a method of estimating the parameters in a linear regression model. Ben-Akiva and Lerman (1985) explained that "the least square estimators are the values that minimise the sum of squared differences between the observed and expected values of the observations". In this study, the dependent variable has binary distribution and error part is not a normal distribution. Since the dependent variable is discontinuous categorical variable, not a continuous variable, the OLS cannot be used in this study. This is because if the OLS were used, the basic assumption of the OLS could run counter to the normality of error term and homoscedasticity (Neter et al., 1989). In general, every normal distribution has the characteristics of being continuous and not having upper and lower value. Therefore, when the dependent variable has the simplest value either zero or one, the dependent variable cannot have a normal distribution. In addition, because the dependent variable is based on the probability, the variance can be calculated from the characteristics of Bernoulli distribution. However, when the variance is calculated by applying error terms, the variance of error (ϵ_i) is not the same and depends on the independent variable X_i. Due to its characteristics, it can be defined as a binary function that the variance of error (ϵ_i) is p_i. When p_i equals 0.5, its variance has the value of maximum (Berry, 1999). On the other hand, when p_i is close to either one or zero, its variance is the minimum. However, the assumption of homoscedasticity contrasts this phenomenon. Consequently, the OLS cannot apply to discontinuous categorical variable of non-linear function.

The method of ML is the most common procedure for estimating the parameter in logit models. To estimate the parameter β, the MLE is normally used. The MLE is a method of estimating the parameters that make the likelihood of the observed results the most probable in the given statistical model (IRMA, 2015). Ben-Akiva and Lerman (1985) explained that "the maximum likelihood estimators are the value of the parameters for which the observed sample is most likely to have occurred." This method is based on the idea that "although a sample could originate from several populations, a particular sample has a higher probability of having been drawn from a certain population than from others" (Ortúzar and Willumsen, 2011). Hence, the MLE is the set of parameters that will generate the observed sample most often. The MLE is designed to maximise the likelihood of reproducing the data given the parameter estimates. Data are entered into the analysis as zero or one coding for the dichotomous outcome. The null hypothesis underlying the whole model alludes that all βs equals zero. A rejection of this null hypothesis means that at least one β does not equal zero (Peng et al., 2002).

Since there is the hypothesis that samples *N* are randomly drawn from a whole population to estimate a model, the likelihood of whole population is the same as the likelihood of observed samples. In this study, a sample of individual *i* will decide mode choice. Independent likelihood function can be given by the product of the model probabilities that individual *i* chooses the option (Agresti, 2002; Czepiel, 2002; Train, 2003):

$$L\ (\beta_1, \beta_2, \cdots, \beta_k) = \prod_{i=1}^{N} (P_{car}^{i})^{y_{car}^{i}} \cdot (P_{PT}^{i})^{y_{PT}^{i}} \tag{3-12}$$

where $\beta_1, \beta_2, \cdots, \beta_k$ is parameter estimates, *N* is the number of samples (total observations), P_{car}^{i} is the probability of car user *i*, P_{PT}^{i} is the probability of PT user *i*, and y_{car}^{i} is $1 - y_{PT}^{i}$, meaning a dummy variable which if respondent *i* chooses a car, it will be one. Otherwise, it will be zero. P_{car}^{i} and P_{PT}^{i} is a function of $\beta_0, \beta_1, \beta_2, \cdots, \beta_k$. If a likelihood function is added by log, the calculation can be easier, and the same result as the function without log can be obtained. Therefore, in order to easily maximise this function, log transformation with both sides can be conducted as follows (Agresti, 2002; Czepiel, 2002; Train, 2003):

$$\begin{aligned} L\ (\beta_1, \beta_2, \cdots, \beta_k) &= \log L(\beta_1, \beta_2, \cdots, \beta_k) = \ln L = \sum_{i=1}^{N} [y_{car}^{i} \cdot \ln P_{car}^{i} + y_{PT}^{i} \cdot \ln P_{PT}^{i}] \\ &= \sum_{i=1}^{N} [y_{car}^{i} \cdot \ln P_{car}^{i} + (1 - y_{car}^{i}) \cdot \ln P_{PT}^{i}] \end{aligned} \tag{3-13}$$

The MLE is the way to search for $\hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_k$ which maximises the log likelihood function ($\beta_1, \beta_2, \cdots, \beta_k$). To do this, the log likelihood function *L* has been differentiated partially with respect to each of the β's and setting the partial derivatives equals to zero ($\beta_k \cdot \frac{\partial L}{\partial \beta_k} = 0$, ($k = 1, 2 \ldots, n$)).

Max $L\ (\hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_k)$

which must satisfy the necessary conditions that (Train, 2003)

$$\frac{\partial L}{\partial \beta_k} = \sum_{n=1}^{N} \{ y_{car}^{i} \frac{\frac{\partial P_{car}^{i}}{\partial \hat{\beta}_k}}{P_{car}^{i}} + y_{PT}^{i} \frac{\frac{\partial P_{PT}^{i}}{\partial \hat{\beta}_k}}{P_{PT}^{i}} \} = 0, \text{ for } k = 1, 2, \cdots, n \tag{3-14}$$

When the first partial derivatives of the equation approach zero and the second partial derivatives are negative, the ML estimates can be obtained. That is, the first partial derivatives of the equation determine the unique maximizer of the function (Flinn, 2004). After confirming the fact that the likelihood function is globally concave ($\frac{\partial L}{\partial \beta_k} \leq 0$), it can be confirmed that $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_k$ is unique ML estimates (Ortúzar and Willumsen, 2011). In this research, the MLE is employed to estimate parameters of models.

3.7.1.4. Logit model with interaction terms

As shown in **Equation 3-1** and **Equation 3-2**, these utility functions illustrate just the main effect of an individual MSP, not the interaction effect of the combined MSPs. Most studies have been interested in only the main effect of the independent variables rather than interaction effect of the independent variables. In general, "the main effects can be defined as the response to passing to the next level of the variable when the rest of the attributes remain constant" (Ortúzar and Willumsen, 2011). On the other hand, the interaction effect between attributes occurs when the magnitude and direction of one independent attribute may depend on the level of the other independent attribute. In this case, one particular attribute may be modified or moderated by the influence of other particular attributes. In this sense, the interaction effect is a sort of conditional effect of occurring "at a specified level of the other explanatory variable" (Gill, 2001). As a result, when the combined effect of two variables is different from the sum of their two main effect utilities, interaction effect occurs (Chrzan and Orme, 2000). Many researchers are interested in understanding the main decision process using a fractional factorial design. A fractional factorial design can be somewhat justified by the following well-known results for linear models (Dawes and Corrigan, 1974):

The main effects typically account for 70 to 90 percent of explained variance,
The two-way interactions typically account for 5 to 15 percent of explained variance,
Higher-order interactions account for the remaining explained variance.

Thus, since interaction effects rarely account for a great deal of the explained variances, only the main effects are mainly considered in practice. However, the interaction effect can significantly influence the probability of each alternative out of all the choice sets. If interaction effect is statistically significant and is excluded from the utility specification, the effects of the MSP may be mistakenly attributed to the single variable (Ortúzar and Willumsen, 2011). In general, in the light of consideration of interaction effects, estimation of all two-way interactions has been used in the most research cases since main effects and two-way interactions account for all the reliable explained variance. In general, the statistical significance of two-factor interaction effect can be tested with a t-test on the coefficients β_{12}, β_{13}, β_{23}, and β_{123} (Ai and Norton, 2003). In this study, the interaction effect is considered in the utility specification to fully understand the modal shift effect of the MSP. The deterministic utility part of utility functions with interaction terms can be described as follows (Rosnow and Rosenthal, 1989; Gill, 2001):

$$V_{i,\,car} = \beta_0 + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j \quad (3\text{-}15)$$

$$V_{i,\,PT} = \beta_1 \cdot Subsidy_j \quad (3\text{-}16)$$

3.7.1.5. Type of models

The data obtained from the questionnaire were used to get the useful information of understanding the modal shift effect of MSP. To this end, nine models with alternative-specific variables are considered. **Table 3-13** shows the criteria for developing various models.

The models are classified according to the difference of scale (level unit or money unit calculated by individual data) and the inclusion of interaction terms. Models A, which are estimated at just the level of survey questionnaires, are models based on the standard of level of the MSP (0, 1, and 2 level). On the other hand, models B, reflects the individual’s PT commuting costs as the survey RP data in order to change the attributes from ‘level unit’ into ‘monetary unit’, are models using money as the unit of account. Through models B, the influence of travel cost variation associated with the MSP can be compared. Models C, reflects not only individual’s PT commuting cost but also individual’s reductions in commuting time concerning the congestion charging, are models using money as the unit of account. All in all, models A are based on the level unit whereas models B and models C are based on the monetary unit.

In the light of interaction terms, models 0 (i.e. model A0, B0, and C0) are models without interaction terms whereas models 1 and models 2 (i.e. model A1, B1, C1, A2, B2, and C2) are models with interaction terms. While models 1 (i.e. model A1, B1, and C1) are models with interaction terms including statistically insignificant coefficients, models 2 (i.e. model A2, B2, and C2) are models with interaction terms comprised of only statistically significant coefficients.

Table 3-13. Criteria for various models

Type		A (level model)	B (cost model)	C (cost model)
· Characteristics of model		· Questionnaire level	· Monetary value derived from questionnaire level (reflect **individual’s data of the travel cost**)	· Monetary value derived from questionnaire level (reflect **individual’s data of the travel cost** + **travel time reductions of congestion charges**)
· Unit of model		· 0, 1, 2 level	· Korean currency (won)	· Korean currency (won)
· Data type of model		· SP	· SP + RP	· SP + RP
0	Model without Interaction terms	A0	B0	C0
1	Model with interaction terms including statistically insignificant	A1	B1	C1
2	Model with interaction terms comprising only statistically significant coefficients	A2	B2	C2

Table 3-14 illustrates the meaning of level of policy variables and the average values of each level. The average value of 50% to the PT commuting cost per day at level one is 2,211 won (£1.23,

2,210.77 won), derived from the survey RP data as respondent's self-reported data, whereas the average value of 100% to the PT commuting cost per day at level two is 4,422 won (£2.46).

Table 3-14. Meaning of the level of variables and average values of each level

<table>
<tr><th rowspan="2">Type of MSP</th><th rowspan="2">Level</th><th colspan="3">Models A</th><th colspan="3">Models B</th><th colspan="3">Models C</th></tr>
<tr><th>A0</th><th>A1</th><th>A2</th><th>B0</th><th>B1</th><th>B2</th><th>C0</th><th>C1</th><th>C2</th></tr>
<tr><td rowspan="3">PT commuting cost subsidy</td><td>0</td><td colspan="3">0 level (=0 %)</td><td colspan="3">0 won</td><td colspan="3">0 won</td></tr>
<tr><td>1</td><td colspan="3">1 level (=50% of public transport commuting cost per day)</td><td colspan="3">Mean: 2,211 won (£1.23)
* Monetary value (travel cost)</td><td colspan="3">Mean: 2,211 won (£1.23)
* Monetary value (travel cost)</td></tr>
<tr><td>2</td><td colspan="3">2 level (=100% of public transport commuting cost per day)</td><td colspan="3">Mean: 4,422 won (£2.46)
* Monetary value (travel cost)</td><td colspan="3">Mean: 4,422 won (£2.46)
* Monetary value (travel cost)</td></tr>
<tr><td rowspan="3">Additional parking fee</td><td>0</td><td colspan="3">0 level (=0 won)</td><td colspan="3">0 won</td><td colspan="3">0 won</td></tr>
<tr><td>1</td><td colspan="3">1 level (=2,500 won, £1.39)</td><td colspan="3">2,500 won</td><td colspan="3">2,500 won</td></tr>
<tr><td>2</td><td colspan="3">2 level (=5,000 won, £2.78)</td><td colspan="3">5,000 won</td><td colspan="3">5,000 won</td></tr>
<tr><td rowspan="3">Congestion charge</td><td>0</td><td colspan="3">0 level (=0 won)</td><td colspan="3">0 won</td><td colspan="3">0 won</td></tr>
<tr><td>1</td><td colspan="3">1 level (=3,000 won, £1.67)
(10% reduction of total travel time)</td><td colspan="3">3,000 won
(10% reduction of total travel time)</td><td colspan="3">Mean: 2,339 won (£1.31)
* Monetary value (reflect travel time reduction from charge)</td></tr>
<tr><td>2</td><td colspan="3">2 level (=6,000 won, £3.33)
(20% reduction of total travel time)</td><td colspan="3">6,000 won
(20% reduction of total travel time)</td><td colspan="3">Mean: 4,677 won (£2.62)
* Monetary value (reflect travel time reduction from charge)</td></tr>
</table>

In order to reflect the value of the reductions in total travel time concerning congestion charges into models C, the data on the values of time[6] and total commuting time from home to work by car (mean: 46 minutes 24 seconds, from 666 samples) are required. The average monetary value that respondents would be willing to pay to reduce their commuting time by ten minutes is estimated as 1,427 won (£0.79) from the survey data (689 samples) as shown in **Table 3-15**. Therefore, the average monetary value of one minute can be approximately calculated as 143 won (£0.079). The average time value is used to obtain the objective results because individual time values are too subjective to use as experimental data. In the survey questionnaire, if the congestion charging is introduced at level one (levy on 3,000 won), a 10% reduction in total travel time is assumed, as a result of the introduction of congestion charges. The average time value of a 10% reduction in total travel time can be calculated by the respondent's individual commuting time value of car use (unit: minute) multiplied by 143 won (average monetary value of one minute). Therefore, **661.27 won** (£0.37) is the average time value of a 10% reduction in total travel time from 666 samples. (For reference, if its values are multiplied by individual's time values instead of 143 won, 656.86 won will be the average time value of a 10% reduction in total travel time from 611 samples). As a result, the average value of level one in congestion charging is **2,338.72 won** (£1.30). In addition, for level two in congestion charging, **1,322.53 won** (£0.73) was calculated as the average monetary value of a 20% reduction in total travel time. Therefore, the average value of level two to congestion charges is **4,677.47 won** (£2.60).

[6] In general, the value of time is the opportunity cost of the time that a traveller spends on his journey. It can be regarded as the amount of money that a traveller would be willing to pay in order to save time, or the amount of money he would accept as compensation for lost time. That is, the sensitivity of an individual to travel time is usually referred to the value of time.

Table 3-15. Result of survey questionnaire: How much would you be willing to pay to reduce your commute time by 10 minutes?

Classification	Sample numbers	Sample ratio (%)
0 won	**31***	4.04
100 won (about £ 0.06)	1	0.13
200 won (about £ 0.11)	6	0.78
300 won (about £ 0.17)	1	0.13
500 won (about £ 0.27)	10	1.30
1,000 won (about £ 0.56)	406	52.93
1,300 won (about £ 0.72)	51	6.65
1,600 won (about £ 0.89)	32	4.17
1,900 won (about £ 1.06)	45	5.87
2,200 won (about £ 1.22)	45	5.87
2,500 won (about £ 1.39)	49	6.39
2,800 won (about £ 1.56)	5	0.65
3,100 won (about £ 1.72)	33	4.30
5,000 won (about £ 2.78)	4	0.52
10,000 won (about £ 5.56)	1	0.13
No response	47	6.12
Total	767	100

* The number of respondents who say clearly 0 won is just five. Since the questionnaires were displayed in the Congestion charge sector, many respondents seem to say ‘no’ as a refusal expression to the introduction of congestion charge policy. These answers were classified as 0 won. However, in terms of utility theory, the answer that time value is zero cannot be acceptable. Therefore, this value is dealt with a missing value in the calculation of average value. In the case of inclusion of responses as a 0 won, the average value of time is 1,365 won (£0.76), instead of 1,427 won (£0.79).

* Source: see **Appendix 1**, section D (3) 4 question.

3.7.2. Development of mixed logit models

3.7.2.1. Introduction

The logit model has been used as a 'workhorse' model for analysing discrete choice data (Hole, 2013) and modelling parameter involving passenger modal choice. However, some drawbacks in the standard logit model arising from intrinsic characteristics are that it should assume that the coefficients are fixed in the population, that the assumption of Independent from Irrelevant Alternative (IIA) holds (meaning that the odds ratio between two alternatives is not changed by inclusion of any other alternative) and that repeated choices made by a respondent are independent (Algers et al., 1998). As a result, the standard logit model (conditional logit model) cannot account for preference heterogeneity (i.e. taste variations) among respondents. That is, it is assumed that respondents have the same preferences or their preferences depend on observable characteristics. Therefore, the assumption that the error terms are independent over utilities and the IIA property may lead to unrealistic predictions. To overcome these drawbacks of the standard logit model, there are many trials to consider more flexible and realistic models such as the MLM, nested logit model, latent class model, multinomial probit model, and heteroscedastic extreme value model (Bhat, 1995).

The MLM can overcome drawbacks by allowing the coefficients in the model to vary across individuals. The MLM is a flexible model that can approximate any random utility model of discrete choice, given an appropriate specification of variables and distribution of coefficients (McFadden and Train, 2000). "It obviates the three limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors" (Train, 2003). The MLM is composed of intrinsic motivation to allow flexible substitution patterns across alternatives (error-components) and unobserved heterogeneity across individuals (random-coefficients) (Bhat, 2001). The MLM extends the conditional logit model by allowing one or more of the parameters in the model to be randomly distributed. Unlike probit that is limited to the normal distribution, the MLM is not restricted to normal distributions and can utilize any distribution for the random coefficients (Train, 2003; Yannis and Antoniou, 2007).

In the case of a binary standard logit model, the IIA property would not be an issue because any other possible alternatives, except for binary choice, are not being studied. In other words, the focus is solely on the choice between car and PT, and other alternatives are not added to the choice set. The IIA property is widely recognized as one of the most serious drawbacks of the standard logit model. It might be argued that one of the advantages of the MLM is that it is unaffected by the IIA property, but this advantage is not required for this research. However, the MLMs are developed to compare the characteristics of various models where taste variations are permitted and to obtain insight into the benefits of more flexible models that represent preference heterogeneity among individuals.

3.7.2.2. Random coefficients reflecting preference heterogeneity

The random-coefficients in the specification of the MLM allows heterogeneity across individuals to exogenous attributes. By allowing β to be random, the MLM is specified. The random utility function of an individual *i* for a choice alternative *k* is given as (Bhat, 2000; Amador et al., 2005):

$$U_{i,k} = V_{i,k} + \varepsilon_{i,k} = \beta_i X_{i,k} + \varepsilon_{i,k} \quad (3\text{-}17)$$

where $X_{i,k}$ is a vector of exogenous attributes (explanatory variables), β_i is a vector of coefficients of these variables for individual *i* representing individual's tastes, and $\varepsilon_{i,k}$ is assumed to be an independently and identically distributed across people and alternatives (type I extreme value error term) (Daly et al., 2012). The terms $X_{i,k}$ is considered non-stochastic, whereas the terms β_i or $\varepsilon_{i,k}$ are not observed and can be considered stochastic. The coefficients (β) vary over individuals in the population with density $f(\beta|\theta)$. This density is a function of parameters θ that show the mean and covariance (standard deviation of the distribution) of the β in the population (Train, 1999). A random scale parameter (β_i) is different from random value of β. β_i stands for the tastes of individuals, these parameters vary over individuals because different individuals have different tastes (Train and Weeks, 2004). Thus, the MLM has different taste coefficients β_is for individual whereas the standard logit model has fixed βs, which implies the βs are the same for every individual. In the MLM, a standard deviation of the coefficient β accommodates preference heterogeneity in the population. This is referred to as unobserved heterogeneity (Hensher and Greene, 2001). In the standard logit model, fixed coefficients ultimately treat the standard deviation as zero. The standard logit model is a special case where the mixing distribution $f(\beta/\theta)$ is degenerated at fixed parameters *b* (Train, 2003). If β is *b*, $f(\beta/\theta)$ will be one. In addition, if β is not *b*, $f(\beta/\theta)$ will be zero. Therefore, all the behavioural information is captured by the mean (Hensher and Greene, 2001). The deterministic component of utility in a linear function can be expressed as (Amador et al., 2005; Algers et al. 1998):

$$V_{i,k} = \beta_i x_{i,k} = (b + z_i)x_{i,k} \quad (3\text{-}18)$$

where β_i is a vector of the coefficient for each individual *i* that varies randomly with tastes and can be expressed as the sum of a population mean (b) and individual deviations (z_i) which shows the individual's tastes associated with the average tastes in the population (Algers et al., 1998; Amador et al., 2005). The choices of unconditional probabilities are given as (Bhat, 2000; Train, 2002):

$$P_{i,k}^{mixed} = \int L_{i,k}(\beta) f(\beta|\theta) d\beta \quad (3\text{-}19)$$

The probability conditional on β_i is given by (Munizaga, 2000; Train, 2003):

$$L_{i,k}(\beta) = \frac{\exp(\beta_i' X_{i,k})}{\sum_i exp\left(\beta_i'{}' X_{i,k}\right)} \tag{3-20}$$

where $L_{i,k}(\beta)$ is the logit formula evaluated with parameter β. Since β_i is random and not known, obtaining condition on β is impossible. However, the unconditional choice probability can be obtained from the integral of $L_{i,k}(\beta_i)$ over all possible variable of β_i (the density of β_i) (Train, 2003):

$$P_{i,k}^{mixed} = \int \frac{\exp(\beta_i' X_{i,k})}{\sum_i exp\left(\beta_i'{}' X_{i,k}\right)} f(\beta|\theta) d\beta \tag{3-21}$$

This is Mixed Logit (ML) probability. The ML probability is a weighted average of the logit function assessed at different values of β, with the weights derived from the density $f(\beta/\theta)$, which has parameter θ (Train, 2003). ML probabilities are the integrals of standard logit probabilities over a density of parameters (Train, 2003). That is, conditional probabilities are integrated over all possible value of β, using the population density of β. ML is a mixture of the logit function calculated at different β with the density $f(\beta/\theta)$ as the mixing distribution (Train, 2003). These form models are called 'mixed logit model' because the choice probability is a mixture of logits with f as the mixing distribution (Brownstone and Train, 1999; Revelt and Train, 1998). Since β_i is a random variable, it can be called the random coefficient logit model (Nevo, 2000). It allows the slopes of utility (i.e., the marginal utility) to be random, which is an extension of the random effect model where only the intercept is stochastic. Any probability density function can be specified for the distribution of the coefficients in the population for $f(\beta|\theta)$ (Felicita and Banu, 2015).

The probabilities do not express IIA, and different substitution patterns are obtained by the proper specification of f (Brownstone et al., 2000). A distribution for coefficients can be specified, and the parameters of that distribution can be estimated. This specification is general since it allows fitting models with both individual-specific and alternative-specific explanatory variables (Hole, 2007).

The most commonly used distribution is normal distribution ($\beta \sim N(b, W)$), allowing coefficients of both signs, due to its simplicity (Revelt and Train, 1998; Albright et al., 2011). In addition, if the coefficient β takes the same sign for every individual, distributions dealing with only one side of zero, like the lognormal (In $\beta \sim N(b, W)$) can be used (Revelt and Train, 1998; McFadden and Train, 2000). When the coefficient cannot be unboundedly large or small, bounded distributions are often used, such as S_b or triangular distributions (Train, 2003). That is, the density of Johnson S_b distribution can be shaped like a lognormal with an upper bound and thinner tails below the bound, but it is more flexible as it can be shaped like a plateau (Ortúzar and Willumson, 2011). In addition, the density of triangular distribution can be shaped like a tent: a peak in the centre and dropping off linearly on both sides of the centre (Hensher and Greene, 2001). Uniform distribution with a (0, 1) bound can be utilized when dummy variables are analysed (Hensher and Greene, 2001; Daly et al., 2012).

3.7.2.3. Error components reflecting heteroscedasticity

A random error term, making correlations among the utilities for different alternatives, is included in the utility specification of the MLM (Train, 2003). The utility of travel mode in the MLM can be divided into a non-stochastic linear-in-parameter terms (i.e. $\beta' X_{i,k}$) that depends on observed data, a stochastic term (i.e. $\mu' \eta_{i,k}$) that is unobserved (non-identical), correlated over alternatives (non-independent) and heteroscedastic over individuals and alternatives, and another stochastic term (i.e. $\varepsilon_{i,k}$) that is independently and identically distributed (IID) over alternatives and individuals (Brownstone and Train, 1999). The utility function with random error terms is as follows (Brownstone and Train, 1999; Brownstone et al., 2000; Train, 2003):

$$U_{i,k} = V_{i,k} + E_{i,k} = \beta' X_{i,k} + E_{i,k} = \beta' X_{i,k} + \mu' \eta_{i,k} + \varepsilon_{i,k} \qquad (3\text{-}22)$$

where $X_{i,k}$ and $\eta_{i,k}$ are vectors of observed variables associated with alternative choice, β' is a vector of fixed coefficients, μ' is a vector of random terms with zero mean that does not vary over alternatives and has density $f(\beta|\theta)$ with parameters θ, $\eta_{i,k}$ is a vector of observed data associated with alternative k, and $\varepsilon_{i,k}$ is a Gumbel error term that does not depend on underlying parameters or data (Hensher and Greene, 2001). The random part of utility is expressed as $E_{i,k} = \mu' \eta_{i,k} + \varepsilon_{i,k}$, which can be correlated in utility over alternatives depending on the specification of $\eta_{i,k}$. The term $\mu' \eta_{i,k}$ can be interpreted as an error component that induces heteroscedasticity and correlation over alternatives in the unobserved portion of utility. Although the elements of μ' are uncorrelated since $V(\mu)$ is diagonal, the unobserved portion of utility is still correlated over alternatives (Brownstone and Train, 1999). The distribution for $\mu' \eta_{i,k}$ can be normal, lognormal, triangular, and so on. Because the standard deviation of a random coefficient is essentially an additional error component, the outcome of estimation is identical (Hensher and Greene, 2001). For the standard logit model, $\eta_{i,k}$ is zero. Thus, there is no correlation in utility over alternatives. The lack of correlation brings about the IIA property and its restricted substitution patterns.

With non-zero error components, utility is correlated over alternatives (Train, 2002):

$$\mathrm{Cov}(\eta_{i,car}, \eta_{i,PT}) = E\,(\mu_i' \eta_{i,car} + \varepsilon_{i,car})(\mu_i' \eta_{i,PT} + \varepsilon_{i,PT}) = \eta_{i,car}' W \eta_{i,PT} \qquad (3\text{-}23)$$

where W is the covariance of μ_i, the utility is correlated over alternatives, even though the error components are independent since W is diagonal (Train, 2003). Since the variance in the error term in the standard logit is greater than the variance in the extreme value component of the error term in the MLM, the normalization makes the parameters in the standard logit model smaller in magnitude than those in the MLM (Revelt and Train, 1998).

3.7.2.4. Unrestricted substitution patterns

The MLM can show general substitution patterns since it does not represent logit's restrictive independence from irrelevant alternatives (IIA) property. The rate of the ML probability ($P_{i,car}/P_{i,PT}$) actively depends on all the data, including attributes of alternatives. In addition, the denominators of the logit function are not cancelled due to the shape of the integrals (Train, 2003). If the *m*-th attribute of one alternative is changed, the rate change of the ML probability of choosing another alternative is given as (Train, 2003):

$$E_{i\,car\,x_{i\,PT}^{m}} = -\frac{x_{i\,PT}^{m}}{P_{i\,car}} \int \beta^{m} L_{i,car}(\beta)\, L_{i,PT}(\beta)\, f(\beta) d\beta = -x_{i\,PT}^{m} \int \beta^{m}\, L_{i\,PT}(\beta) \left[\frac{L_{i\,car}(\beta)}{P_{i\,car}}\right] f(\beta) d\beta \qquad (3\text{-}24)$$

where $x_{i\,PT}^{m}$ is the *m*-th vector of observed variables for a PT user *i* and "β^{m} is the *m*-th element of β. The elasticity is different for each alternative. That is, a 10% reduction for one alternative does not imply a 10% reduction of other alternative. Rather, the substitution pattern depends on the specification of the variables and mixing distribution" (Train, 2003). That is, the percentage change in the probability depends on the correlation between the likelihood that respondent *i* will choose alternative car ($L_{i,car}$) and the likelihood that respondent *i* will choose alternative PT ($L_{i,PT}$), over different values of β. All in all, since mixing distribution allows the coefficient of the variable to vary, the correlation between $L_{i,car}$ and $L_{i,PT}$ leads to different substitution patterns.

3.7.2.5. Simulation

The MLM is suitable for a simulation method of estimation. Since the integral in the ML probability does not have a closed form, a numerical approximation by using simulation is needed (Train, 1999; Revelt and Train, 1999). The probabilities can be approximated through simulation for any given value of θ. First, draw a value of β from the density f($\beta|\theta$), and label it β^{r} with the superscript *r*, meaning the *r*-th draw. Second, calculate the logit function $L_{i,k}(\beta^{r})$ with the draw. Third, repeat the process many times and obtains the average value of the results (Train, 2003). The average value of the simulated probability can be calculated in the following way (Bhat, 1998; Train, 1999):

$$\check{P}_{i,k} = \frac{1}{R}\sum_{r=1}^{R} L_{i,k}(\beta^{r}) \tag{3-25}$$

where R is the number of reiterations. $\check{P}_{i,k}$ is an unbiased estimator of the likelihood function $P_{i,k}$. As R increases, its variance decreases (Bhat, 2000). The simulated probabilities are put into the log-likelihood function to create the Simulated Log-Likelihood (*SLL*) function (Bhat, 2000):

$$SLL = \sum_{i=1}^{I}\sum_{k=1}^{K} d_{i,k,s} \ln \check{P}_{i,k} \tag{3-26}$$

where $d_{i,k}$ will be one if an individual i chooses k (car or PT) in the choice situation s and zero otherwise. The maximum *SLL* estimator is the value of θ that maximizes the *SLL*. That is, the parameters θ can be estimated by maximising the *SLL* function (Bhat, 2000). Usually, different draws are taken for each observation. This process maintains independence over decision makers of the simulated probabilities that enter the *SLL*. For independent draws from density *f*, the simulated probability is unbiased and consistent for the true probability (Sandor and Train, 2004).

Since the log transformation of $\check{P}_{i,k}$ is non-linear, the estimator is biased. That is, the maximum *SLL* estimator will be "a biased simulation of the maximum log-likelihood estimator because of the logarithmic transformation in the log-likelihood function" (Bhat, 2000). "The bias decreases if *R* increases faster than the squared root of the number of observations" (Staus, 2008), the estimator is asymptotically equivalent to the maximum *SLL* estimator (McFadden and Train, 2000; Brownstone et al., 2000; Staus, 2008). The maximum *SLL* estimator is consistent, asymptotically efficient and asymptotically normal (Lee, 1992). The specification is generalized to allow for repeated choices by each sampled individual. The specification treats the coefficients that enter utility as varying over people, but being constant over choice situation for each person.

The Halton drawings are designed to give fairly even coverage over the domain of the mixing distribution to reduce the number of draws. Halton sequences are based on prime numbers. "For each element of each sequence, the inverse of the cumulative mixing distribution is calculated. The resulting values are Halton draws from the mixing distribution" (Train, 1999). The number of Halton draws that are used in the simulation does not seem to affect the result if more than 100 draws are used (Revelt and Train, 1998). Bhat (1998) found that the simulation error (variance) in the estimated parameters was lower using 100 Halton numbers than 1,000 random numbers. By using 125 Halton draws, Bhat (1998) found the simulation error to be half as large as with 1,000 random draws and smaller than with 2,000 random draws (Train, 1999). Therefore, 100 Halton draws are used in this study.

3.7.3. Review of nested logit models

The nested logit model has been usually developed to overcome a drawback of standard logit assuming that that the assumption of IIA holds. A nested logit model has a hierarchical structure to see the correlation of unobserved attributes by forming mutually exclusive and collectively exhaustive choice set to relax the IIA assumption (Williams, 1977; Daly and Zachary, 1978; Dissanayake and Morikawa, 2001a). In the nested logit model, the set of similar alternatives can be partitioned into subsets, called nests. IIA holds within each nest but not across nests. That is, while the ratio of probabilities is independent of the other alternatives in the same nest, the ratio of probabilities can depend on the attributes of other alternatives in the different nests (Train, 2003). In **Figure 3-3**, each branch represents a subset of alternatives and every leaf on each branch denotes an alternative (Train, 2003). If there are two options that are similar to each other and one option which is different from the two others at the same time out of three options, a nested logit model can be calibrated[7]. Each nest shares common component of random utility and alternative specific random

[7]The utility of composite utility is composed of 'the Expected Maximum Utility (EMU)' and 'the vector **X** of attributes which are common to all members of the nest EMU' (Williams, 1977). The composite utility of the nest is V_i= σ EMU + α **X**, where σ *and* α are parameters. EMU = $\log\sum_i EXP(Z_i)$, where Z*i* is the utility of alternative *i* in the nest (Ortúzar and Willumsen, 2011).

At the lower nest, a binary logit model with regard to the utility of bus and subway is given by:

$$P\ (Bus\ /\ PT) = \frac{EXP\ (Z_{Bus})}{EXP\ (Z_{Subway}) + EXP\ (Z_{Bus})}, \qquad P\ (Subway\ /\ PT) = 1 - P\ (Bus\ /\ PT)$$

where the utilities Z include only the elements which are not common to both modes. The utility of PT is $V_{PT} = \sigma$ EMU + $\sum_g \alpha_g X_g$, where EMU = ln [exp (Z_{subway}) + exp (Z_{Bus})] and the summation over g regards all the common elements X. The structural parameter σ should be placed between zero and one ($0 < \sigma \leq 1$) (Williams, 1977; Ben-Akia and Lerman, 1985). First, if σ is less than zero ($\sigma < 0$), a rise in the utility of an alternative within the nest would reduce the probability of the nest. Second, if σ is equal to zero ($\sigma = 0$), a rise would not influence the probability of the nest. Third, if σ is more than one ($\sigma > 1$), a rise in the utility of an alternative within the nest would go up the probability of the nest. Fourth, if σ equals to one ($\sigma = 1$), indicating complete independence (no correlation) within nest g, the model becomes equivalent to a standard logit model (Dissanayake and Morikawa, 2001a; Train, 2003; Ortúzar and Willumsen, 2011).

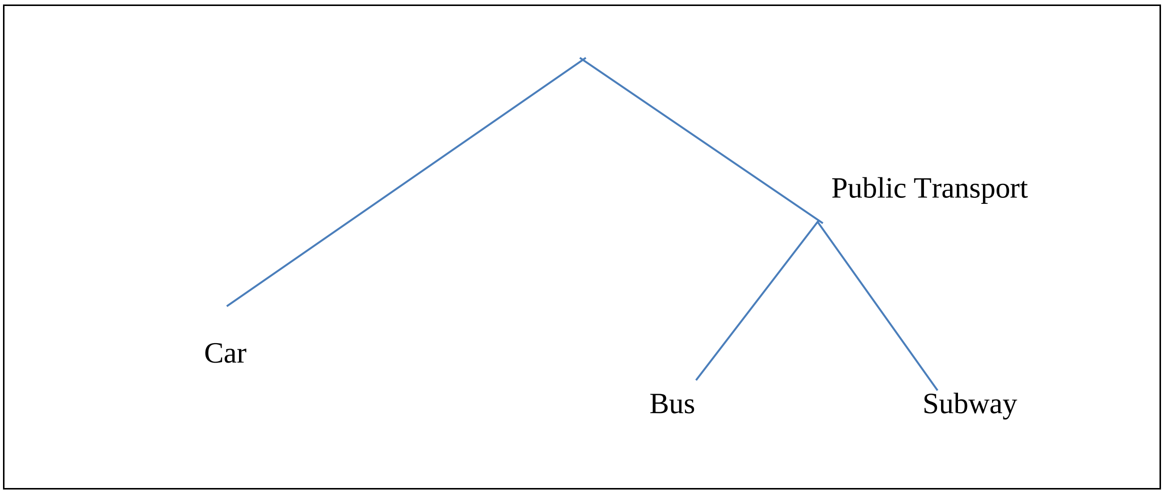
At the higher nest, a binary logit model with regard to the utility of car or PT is the same form as in a standard logit model, as in the following:

$$P\ (Car) = \frac{EXP\ (V_{Car})}{EXP\ (V_{Car}) + EXP\ (V_{PT})}, \qquad P\ (PT) = 1 - P\ (Car)$$

The choice probability of choosing the nested alternative can be obtained by multiplying 'the marginal choice probability (in the higher nest)' by 'the conditional choice probability (in the lower nest)' (Koppelman and Bhat, 2006). In conclusion, the choice probabilities of each option in a nested logit model are as follows:

P_{Car} = P (Car), P_{Bus} = P (Bus/PT) · P (PT), P_{Subway} = P (Subway/PT) · P (PT) component (Dissanayake and Morikawa, 2001a). The simultaneous estimation method is usually used.

Figure 3-3. Tree diagram for mode choice



If there are so many alternatives in the standard logit model, the occurrence of IIA property can occur. That is, if there are three choice options such as a car, bus, and subway, a nested logit model can be calibrated. However, since a choice set in this research is limited to binary choice: 'car' and 'PT[8]', a nested logit model cannot be calibrated.

[8] In terms of commuting pattern in the Gangnam area of Seoul, there is an ambiguous distinction between bus and subway. As shown in **Table 4-4**, since the rate (25%) of the commuters who use two PT modes (e.g. bus + subway) is higher than bus users (16.8%) or subway users (12.8%) in Seoul, it can be inferred that many commuters used to transfer between bus and subway or use indistinctly either bus or subway.

3.8. Hypothesis Testing and Goodness of fit of estimated model

In general, the validity of an estimated coefficient can be reviewed by a t-test (t-statistic) as a statistical hypothesis test. To test a hypothesis about the estimated coefficient, the t-test can be commonly used in discrete choice models (Train, 2003). The t-test is to examine whether the null hypothesis (H_0) that an estimated coefficient value (β) is equal to zero is acceptable at the proscribed significance level. That is, the t-test is used to determine whether an estimated coefficient value is significantly different from zero, assuming a normal distribution. In this case, the hypothesis is used as follows:

H_0: β_k = 0, H_1: $\beta_k \neq$ 0, k = 1, 2, 3, ------------- , K (3-27)

An absolute t-value greater than 1.96 is acceptable at the 95% confidence interval for a two-tailed test. In addition, if the absolute t-value is greater than 2.57, it is statistically acceptable at the 99% confidence interval. The higher the absolute t-value, the greater the confidence. A high absolute t-value indicates that the null hypothesis (H_0) is rejected and the independent variable has a statistically significant effect on the dependent variable. Therefore, it can be interpreted that the coefficient has a high level of predictive power. In this research, the coefficients in the utility function are confirmed by evaluating the t-test, which shows that hypothesis is rejected at 5% level of significance. It is basically hypothesized that the coefficients related to the MSP and explanatory variables affect the mode choice behaviour significantly. That is, the assumption is that mode choice (modal shift) mainly depends on the other level of MSP variables and other explanatory variables.

For more complex hypotheses, a likelihood ratio test can be used (Train, 2003). A null hypothesis (H_0) is expressed as constraints on the values of the coefficient. The maximum likelihood estimate of the parameters ($\hat{\beta}$) is that value of β that gives the highest value of L without violating the constraints of the null hypothesis(H_0). The ratio of likelihoods, ($R = \frac{\hat{\beta}^{H_0}}{\hat{\beta}}$), where $\hat{\beta}^{H_0}$ is the maximum value of the likelihood function under the null hypothesis(H_0), and $\hat{\beta}$ is the unconstrained maximum of the likelihood function (Train, 2003).

H_0 : $\beta_k = \beta_1 = \beta_2$ ------------ $= \beta_k = 0$
H_1 : It is not true that all the β_k are 0. (3-28)

The test statistic is $-2[L(\hat{\beta}^{H_0}) - L(\hat{\beta})] = -2[L(0) - L(\hat{\beta})]$, defining that $-2 \log R$ is distributed X^2 with degrees of freedom is equal to the number of restrictions implied by the null hypothesis. Since the log likelihood is always negative, this is simply two times the difference between the constrained and unconstrained maximums of the log-likelihood function. If this value exceeds the critical value of X^2 with the appropriate degrees of freedom, then the null hypothesis is rejected (Train, 2003).

Meanwhile, to judge whether the estimated discrete choice model can explain the observed SP data effectively, the validity of the model can be tested by certain criteria. The goodness of fit for total models can be verified by the Likelihood Ratio index (LR, ρ^2, rho-squared index). The ρ^2 can be commonly used to assess how well the estimated model fits or explains the observed data. In particular, the comparison of the ρ^2 is based on the concept that higher value of the ρ^2 can be interpreted as a superior model. The ρ^2 is defined by the formula (Ortúzar and Willumsen, 2011):

$$\rho^2 = 1 - \frac{L(\widehat{\beta})}{L(0)} \tag{3-29}$$

where $L(0)$ is the value of the log likelihood function when the values of all of the coefficients (β_1, β_2, $\cdots$, β_k) are zero. In addition, $L(\hat{\beta})$ is the maximum value of log likelihood function. $L(0)$ is seen as the log likelihood of a model which the probability of choosing each alternative is a half out of two alternatives. In other words, the ρ^2 compares 'the log-likelihood of a model with all the coefficients calculated to maximum values ($L(\hat{\beta})$)' to 'the log-likelihood of a model with all the coefficients restricted to zero ($L(0)$)'. The ρ^2 has values in the limit between zero (no fit) and one (perfect fit). The ρ^2 values around 0.4 are usually considered excellent fits (Vedagiri and Arasan, 2009; Ortúzar and Willumsen, 2011). Normally, the acceptable ρ^2 value range from 0.2 to 0.4 is considered a good fit model. The closer to 1 the value, the better the validity of the model. Because the ρ^2 may, in principle, be computed relative to any null hypothesis, it is important to choose an appropriate one.

3.9. Summary

In this chapter, the difference between quantitative and qualitative, aggregate and disaggregate, and SP and RP approaches is reviewed to determine the method of the research appropriately. The three MSPs are decided as alternative-specific variables (attribute), and the levels of each attribute are determined. The significant factors affecting travel mode choice are selected as explanatory variables. These factors include socio-demographic, travel, and attitudinal characteristics. The main experimental design is also settled as a full factorial design to investigate the two-factor interaction effects of MSP. Survey location is selected as Gangnam area in Seoul since this area is one of the most congested areas as well as being well-equipped with PT facilities and services. The sample size is determined on more than 384 samples. Modelling tools such as standard logit model, MLM, and nested logit model are explained. To calibrate appropriate models, the method of maximum likelihood is reviewed, and the criteria for the various types of models are illustrated. Also, the theoretical framework for hypothesis testing and goodness of fits of the model are explained.

Chapter 4. Data Review of Data Requirement and Collection

4.1. Introduction

This chapter presents the process and results of an online survey. This chapter comprises three further sections. Section 4.2 shows an overview of the survey process. Section 4.3 investigates the representativeness of samples. Section 4.4 illustrates major information from the survey.

4.2. Overview of Online Survey

The survey has been carried out by an online survey[9] (*i*-Survey[10]) from 1 Jan 2013 to 25 Mar 2013 (see **Table 4-1**). The pilot survey (ID 6310, 1 Jan 2013~10 Jan 2013) had been conducted to improve the quality of the questions in light of responses received. According to the indications of some respondents, the deployment of the SP survey and some questions involving possible individual privacy have been adjusted or corrected.

Thereafter, the main survey has been carried out from 17 Jan 2013 to 25 Mar 2013. The four types of SP survey, comprised of the different order of 27 choice questions, have been displayed to reduce possible measurement error (see **Appendix 1. section B (1)**).

Table 4-1. Implementation of online survey

Type of questionnaire	i-Survey research ID	Survey term	Number of respondents
Pilot survey	6310	2013. 1. 1 ~ 2013. 1. 10	22
A type (first survey)	6658	2013. 1.17 ~ 2013. 1. 31	45
A type	6837	2013. 2. 4 ~ 2013. 3. 25	174
B type	6852	2013. 2. 5 ~ 2013. 3. 24	93
C type	6867	2013. 2. 6 ~ 2013. 3. 25	352
D type	6873	2013. 2. 7 ~ 2013. 3. 20	120
Total (valid data)		**2013. 1. 1 ~ 2013. 3. 25**	**806 (784)**

[9] Although online survey at the initial stage can be more complex and take a longer time than face-to-face survey, the limitation of time and cost can be overcome more easily. In addition, the data coding and storage is easier than other survey methods.

[10] *i*-survey is survey generation and research tool for distributing online questionnaire. It is free to use it if the researcher is a member of the University of Southampton. The researcher can send a customised email to participants. If a respondent touches the slider, respondent's responses will be stored.

A respondent was a commuter who worked in the Gangnam area with a driving license and an available car. The lists of companies and institutes which are based in the Gangnam area have been obtained from the central or local government as a sampling frame. Altogether, 550 companies out of 15,000 listed have been selected by a random sampling method (using an Excel program). The researcher contacted the selected companies and institutes by phone. Some people agreed to participation in the survey and sent lists of employees' e-mails or redistributed invitation e-mails (i.e. online questionnaire) to their employees, while some rejected the request for participation. In addition, the personnel staff, bosses, or respondents who participated in this survey were requested to redistribute the invitation e-mail. Therefore, some on-line questionnaires might be redistributed by e-mail or Facebook because some respondents wanted to help the survey or to provide the possibility of entering into a prize draw. It can be assumed that there may be some 'snowball sampling' in the redistribution process since invitation e-mails can be unlimitedly redistributed (see **Table 4-2**).

The survey has been mainly conducted by the participation of more than 100 companies or institutes. Although the researcher has already deleted the unfinished survey files to avoid confusion during data processing, it can be estimated that the number of people who opened the *i*-Survey is approximately 3.5 times more than that of respondents who fully completed the survey. About 200 people who answered many questions had left it during the survey. If anyone who received an email or invitation card had no interest in this survey, they would not open *i*-Survey. 'Not open' cannot be counted. Therefore, the exact response rate cannot be measured due to the characteristics of the online survey method. Finally, 784 people took part in the survey validly (see **Table 4-1**).

Table 4-2. How to know about the online survey

Classifi-cation	Participation chance	Sample number	Sample ratio (%)	Type of sampling
Valid	Employer's email	436	56.2	Random sampling
	Invitation card at lunchtime	4	0.5	Convenience sampling
	An acquaintance told the respondent about it	316	40.7	Snowball sampling
	None of above	18	2.3	
	Total	774	99.7	
Missing	No response to SP survey	2	0.3	
Total		776	100	

The respondents who do not belong to the survey target group were 8 out of 784. They consisted of two respondents whose workplace was not in the Gangnam area and six respondents whose home was in the Gangnam area, not the workplace. Therefore, eight samples have been removed from the subject of the research. In addition, since there were six respondents who always took a walk as a commute mode and two respondents who had no responses to SP choice survey, nine respondents have been excluded from the model estimation. Therefore, the response data of 767 respondents have been used in the development of logit models because this research focuses on the change of mode choice from car to PT.

From the samples, 29.8% of respondents chose PT while 70.2% of respondents chose a car as a commute mode at present. However, it does not mean that many commuters in the Gangnam area are using a car in everyday life. The survey target was anyone who has a driving licence and an available car for commuting officially. However, in the questionnaire, when a respondent uses a car more than once out of 10 days as a commute mode, it was supposed that the respondent should answer as 'the use of a car'. Therefore, what the respondent answered the use of a car meant that he or she used a car as a commute mode more than once out of ten days. As shown in **Table 4-3**, car users are less than PT users in reality.

Table 4-3. The use of commute mode between home and work or school (2011) (unit: %)

Classification	Gangnam-Gu	Seocho-Gu	Seoul
Car	26.8	39.5	26.0
Bus	12.5	13.3	16.8
Subway	16.5	14.3	12.8
Bus + Subway	24.5	20.9	25.0
Car + PT	2.7	2.4	3
Taxi	0.6	0.3	0.2
Cycle	1.0	1.6	2.1
Walk	14.7	7.5	13.2
Other	1.1	0.2	0.8

* Source: Seoul city statistics<from http://stat.seoul.go.kr>

4.3. Representativeness of Samples

As indicated in **Table 4-4**, the location ratio of respondent's workplace (Gangnam-Gu 61.5%, Seocho-Gu 38.2%) in survey corresponds approximately to the current worker ratio of the Gangnam area (Gangnam-Gu 61.5%, Seocho-Gu 38.5%). These data indicate the good distribution of survey indirectly.

Table 4-4. Location of respondent's home and workplace

Location	Region	Sample number	Sample ratio (%)	Current data (worker ratio in the Gangnam area) (%)
Location of respondent's home	Seoul City	466	60.8	
	Gyunggi province	279	36.4	
	Incheon City	16	2.1	
	Gangwon province	1	0.1	
	No response	5	0.7	
Location of respondent's workplace	Gangnam-Gu	472	**61.5**	**61.5**
	Seocho-Gu	293	**38.2**	**38.5**
	No response	2	0.3	
Total		767	100	

The researcher has not discovered statistics related to the disabled commuters who work in the Gangnam area yet. Alternatively, there are residential statistics involving the disabled people who live in the Gangnam area. As shown in **Table 4-5** and **Table 4-6**, there are no major differences between the samples (2.9%) and proxy population (2.6%). Considering these statistics, it can be concluded that the representativeness of samples is acceptable.

Table 4-5. Number of the disabled worker in the survey

Individual characteristics	Classification	Sample number	Sample ratio (%)
Whether or not the respondent is disabled	Yes	22	**2.9**
	No	738	96.2
	No response	7	0.9
Total		767	100

Table 4-6. Number of the disable lives in the Gangnam area (2012)

Classification	Total population	Disabled population	Percent
Gangnam-Gu	569,997	15,641	2.7
Seocho-Gu	439,998	10,702	2.4
Sum	1,009,995	26343	**2.6**

4.3.1. Low participation of female workers

According to Seoul's report of the census on developments, as of 2011, the ratio of a female worker in the Gangnam area is 39 %. On the other hand, just 15 % of respondents in this survey are female (see **Table 4-7**). At a glance, it seems that the samples have a major bias.

However, the overall picture in South Korea is that most of the drivers are usually men while most of the women tend to use a PT. This is a kind of cultural phenomenon under the influence of traditional patriarchal society and Confucian culture. Another factor may be women's employment or work patterns. Although the ordinary companies in South Korea tend to employ young women, many women who can afford to drive a car usually leave the company after childbirth because of the lack of a nursery care system and cultural emphasis on child education with a mother during the childhood. Another factor is that a female worker does not have time to participate in the online survey which takes about 30 minutes. Working women are usually busy doing household affairs as well as businesses under the influence of Confucian culture.

4.3.2. High proportion of people in their 40s

People in their 40s occupy 45.8% of respondents. It is an understandable thing that many people who can afford to drive in the Gangnam area are in their 40s. This research focuses on the modal shift from car to PT. Therefore, many respondents should be car users to measure the modal shift effects of the MSP. In South Korea, the largest proportions of the main labour force are in their 30s and 40s. Healthy men in their 20s have the duty of national service for two years, and about 80% of people in their 20s enter university. In particular, the unemployment of young people is the highest these days. In addition, many people in their early 50s should be retired under company pressure in reality because South Korea is an early retirement society.

Table 4-7. Individual and social characteristic data of the survey respondents

Individual characteristics	Classification	Sample number	Sample Ratio (%)
1) Gender	Male	647	**84.4**
	Female	113	14.7
	No response (missing value)	7	0.9
2) Age	Less than 20s or 20s	30	3.9
	30s	253	33.0
	40s	346	**45.1**
	50s	119	15.5
	60s or more than 60s	11	1.4
	No response (missing value)	8	1.0
3) Educational career	No education	1	0.1
	High school	22	2.9
	College	24	3.1
	University	493	**64.3**
	Postgraduate school	222	28.9
	No response (missing value)	5	0.7
4) Occupational sector	Governmental sector	24	3.1
	Specialized sector	171	22.3
	Administrative or clerical sector	319	**41.6**
	Technical sector	127	16.6
	Sales sector	19	2.5
	Service sector	58	7.6
	Production, drive or labour sector	1	0.1
	Other	44	5.7
	No response (missing value)	4	0.5
5) Respondent's household size (the number of family member)	1	38	5.0
	2	78	10.2
	3	185	24.1
	4	366	**47.7**
	5	81	10.6
	6	9	1.2
	7 or more	6	0.8
	No response (missing value)	4	0.5
6) How many workers are in your household?	1	383	**49.9**
	2	316	41.2
	3	62	8.1
	No response (missing value)	6	0.8
7) Whether or not the respondent has a child who commutes nursery facilities or school	Yes	377	**49.2**
	No	383	49.9
	No response (missing value)	7	0.9
Total		767	100.0

4.3.3. Highly educated workers

Most of the respondents have university degrees. In recent years, 80% of high school graduates tend to enter university in South Korea. The society became a highly-educated one because of the influence of Confucian culture and education-background-focused society. In particular, the Gangnam area is considered as a new central business district with the highly-educated people.

4.3.4. Sedentary workers

Due to the characteristics of the on-line survey, 42% of respondents working in the administrative or clerical sector took part in this survey. Most of the respondents answered the questionnaires in their office during lunchtime. It can be assumed that most workers in the sales, service and production, drive and labour sectors did not find the time to participate in this survey during the work hour. For physical workers, participating in the online survey is a not easy thing. In the meantime, since many physical workers can't afford to drive a car as a commute mode, they might think that they are not suitable for this survey and, therefore, did not participate in. In conclusion, the majority of respondents are sedentary workers.

4.3.5. High household income

In terms of household income, the distribution of respondents is even. However, the level of respondents' household income is higher than the average household income of Seoul city residents. **Table 4-8** compares the average household income of survey respondents with the average household income of Seoul city residents. The Gangnam area is one of the wealthiest regions in South Korea. Many of the internationally known companies like Samsung, LG and so on are located in the Gangnam area in South Korea.

Table 4-8. Total household income from all sources before tax per month

Level of household income	Sample number	Sample ratio	Seoul city data
Up to 1,000,000 won (= £550)	1	0.1%	3.9%
1,000,001~2,000,000 won (= £551~£1,100)	16	2.1%	11.6%
2,000,001~3,000,000 won (= £1,101~£1,650)	57	7.4%	19.0%
3,000,001~4,000,000 won (= £1,651~£2,200)	137	17.9%	25.3%
4,000,001~5,000,000 won (= £2,200~£2,750)	132	17.2%	20.0%
5,000,001~6,000,000 won (= £2,751~£3,300)	125	16.3%	20.1%
6,000,001~7,000,000 won (= £3,301~£3,850)	100	13.0%	
7,000,001~10,000,000 won (= £3851~£5,510)	141	**18.4%**	
More than 10,000,001 won (= over £5,511)	55	7.2%	
No response (missing value)	3	0.4%	
Total	767	100%	100%

* Source: 2012 Seoul survey (urban policy indicator survey), 2013. 6. 17.

4.4. Analysis of Survey Data

The average distance between home and workplace is 18.56 km. The average car-using day of car users a week is 3.04 day. The number of commuters who have free parking or full supported parking fee from company is 479 respondents (62.5%) whereas the number of commuters who receive commute grants or support from company is 144 respondents (18.8%).

While the average commuting time for car users is 46 minutes 24 seconds (666 samples), the average commuting time for PT users is 60 minutes 25 seconds (695 samples). In addition, the average commuting time for PT users in this survey (60 minutes 25 seconds) corresponds approximately to the results of another survey (65 minutes) in **Table 4-9**.

Table 4-9. Commuting time with PT users

Classification	From Seoul to Seoul	From Gyunggi province or Incheon city to Seoul	Average commuting time from home to work
Average time	51 minutes	78 minutes	65 minutes

* Source: The Seoul Institute (2012) User traffic patterns traffic card linkage analysis methods.

When a commuter uses PT, the rate of waiting time out of total commuting time is 12.83% (from 636 responses). The rate of the transfer time is 13.41% (from 380 responses). On the other hand, when a commuter uses a car, the rate of parking time in the workplace or around the office out of total commuting time is 8.29% (from 639 responses). The rate of walking time from the parking lot to office is 9.19% (from 633 samples). The commuting cost of car users from home to work is about 6,097 won (£ 3.39) (from 619 responses), whereas the commuting cost of PT users is 2,211 won (£ 1.23) (from 678 responses). These data will be used as possible explanatory variables in the models.

Table 4-10 shows the opinions about the introduction of the congestion charge. When congestion charges are introduced, the majority of respondents answered that the most appropriate cordon in Seoul city is a joint introduction of the Gangnam area (new CBD) and 4 big gate area (old CBD). In addition, the majority of respondents said that appropriate level of congestion charges per day is 2,000 won (the lowest level in the optional questionnaire). Also, the majority of respondents answered appropriate application time is either 07:00 ~ 10:00 or 07:00 ~ 21:00 (193 samples 25.2% respectively).

Table 4-10. Information about congestion charges from the SP survey

Question	Response item	Sample number	Sample ratio
If congestion charge should be introduced, what is the most appropriate cordon in the Seoul city?	Gangnam area (Gangnam-Gu, Seocho-Gu)	135	17.6
	Four big gate area (Jongro-Gu, Jung-Gu)	205	26.7
	Gangnam and four big gate area	**397**	**51.8**
	Other	23	3.0
	No response	7	0.9

If congestion charging should be introduced, what is the appropriate level of congestion charge per day?	2,000 won (= £ 1.1)	**392**	**51.1**
	3,000 won (= £ 1.65)	172	22.4
	4,000 won (= £ 2.2)	18	2.3
	5,000 won (= £ 2.75)	100	13.0
	6,000 won (= £ 3.3)	12	1.6
	7,000 won (= £ 3.85)	5	0.7
	8,000 won (= £ 4.41)	3	0.4
	9,000 won (= £ 4.96)	24	3.1
	Other	33	4.3
	No response	8	1.0
If congestion charge should be introduced, what is the appropriate application time?	07:00 - 18:00	155	20.2
	07:00 - 21:00	**193**	**25.2**
	07:00 - 15:00	11	1.4
	07:00 - 10:00	**193**	**25.2**
	10:00 - 17:00	67	8.7
	17:00 - 21:00	60	7.8
	12:00 - 21:00	3	0.4
	Other	71	9.3
	No response	14	1.8
Total		767	100 (%)

As shown in **Table 4-11**, the vast majority of respondents (23%) answered by saying that the most effective and acceptable MSP in the short term (1 ~ 2 years) is to improve the quality of PT service. This result matches to the previous research (Kingham et al., 2001). That is, the quality of PT service can be a key factor to encourage people to switch a commute mode. In general, a frequent, reliable, convenient and cheap PT system may attract many people. In addition, the majority of respondents (24.2%) answered that the most effective and acceptable MSP in the long term (more than five years) is improving the PT facilities. Through the result of the optional questionnaire, it can be understood that improving the quality of PT service and improving facilities are the most important factors for the most effective and acceptable MSP.

Table 4-11. Opinion on MSP in the optional open questionnaire

Content	Response item	Sample number	Sample rate(%)
The most effective and acceptable MSP in the short term (1-2 years)	Strengthening parking control (e.g. strengthening the 10th-day-no-driving system etc.)	160	10.4
	Increasing parking fee	54	3.5
	Levying congestion charge on a certain cordon	329	21.4
	Providing commute cost subsidy from the company	195	12.7
	Increasing fuel price	49	3.2
	Holding travel awareness campaigns	24	1.6
	Stimulating car sharing or car pooling	61	4.0
	Providing more available travel information	118	7.7
	Improving the quality of PT service	**365**	**23.8**
	Other	15	1.0
	No response	166	10.8

The most effective and acceptable MSP in the long term (more than Five years)	Reducing parking space close to workplace	28	1.8
	Increasing car operating cost	56	3.7
	Constructing new subway or BRT	329	21.4
	Constructing 'park and ride' outside the urban area	197	12.8
	Improving PT facilities	**371**	**24.2**
	Bicycle revitalization	48	3.1
	Transit-Oriented Development (e.g. car free development)	142	9.3
	Substitution of communications for travel (e.g. teleworking, E-shopping)	33	2.2
	Spread alternative working patterns (e.g. flex time)	157	10.2
	Other	13	0.8
	No response	160	10.4
Total	A respondent can tick up to two (767X2=1534)	1534	100 (%)

Table 4-12 shows the reason of car use or PT use in the commuting journey and priority to improve PT. The majority of respondents answered that the reason of car use in the commuting journey is to save travel time whereas the reason of PT use is to save money related to car operating cost such as fuel and toll. In addition, the majority of respondents (21.8%) answered that the priority to improve PT is faster services of PT. Therefore, it can be concluded that the improvement of PT to get faster services is a crucial factor to improving the quality of PT.

Table 4-12. Reason for car use or PT use in the commuting journey and priority to improve PT

Content	Response item	Sample number	Sample rate(%)
Reason for using a car in the commuting journey	To save travel cost	23	1.5
	To save travel time	**317**	**20.7**
	Because of the limitation of access to PT (e.g.: too far from home)	71	4.6
	Because of the difficulty of transfer in using PT	28	1.8
	Because of the convenient, comfortable and clean atmosphere in car (e.g.: disliking crowded bus or subway)	204	13.3
	Because of no need of taking a walk	48	3.1
	Because of no need of waiting for a bus or a train	93	6.1
	Because of the need of using car to do business or individual purpose during the work hour	261	17.0
	Because of the frequent of extra work after working hours	30	2.0
	To carry other people (e.g. carpooling, to commute to school for children)	18	1.2
	Other	18	1.2
	No response	422	27.5
Reason for using PT in the commuting journey	Because of the limitation of parking space or parking access in the workplace	166	10.8
	Because of the expensive parking fee	51	3.3
	To save money related to car operating cost such as fuel and toll.	**326**	**21.3**
	To save travel time	93	6.1
	To enjoy extra time while commuting (e.g. sleeping, playing mobile game)	75	4.9
	To secure the punctuality to work	115	7.5
	To contribute to the environmental protection	20	1.3
	To reduce stress from while driving (e.g. disliking driving, congestion problems)	104	6.8
	To secure the safety	11	0.7
	Because of the frequent extra-activities after work hour (e.g. alcohol consumption)	139	9.1
	Other	36	2.3
	No response	398	25.9

Priority to improve PT	Faster services (e.g. provision of faster trains or buses, expansion of exclusive bus lane)	**335**	**21.8**
	More frequent services (e.g. reduction of headway intervals)	236	15.4
	Better connection with the same or other PT (e.g. transfer improvement, change of bus route)	173	11.3
	Reducing overcrowding and the provision of sufficient seats	290	18.9
	Improving station or bus stop access (e.g. construction of moving walk and escalator, more shuttle bus)	82	5.3
	Cheaper fares (e.g. sales of discount tickets)	101	6.6
	Reliable services (e.g. on time services)	69	4.5
	Nicer vehicles and facilities (e.g. improving air condition or noise, clean restroom, proper temperature)	70	4.6
	More available information (e.g. providing more route information, arrival/departure information)	6	0.4
	Improving security (e.g. more CCTV cameras)	4	0.3
	Other	0	0
	No response	168	11.0
Total	A respondent can tick up to two (767X2=1534)	1534	100 (%)

4.5. Summary

The survey has been carried out by an online survey (*i*-Survey) from 1 Jan 2013 to 25 Mar 2013. Through the survey, 767 respondents validly answered. Although the proportions of some factors such as gender, highly educated workers, and sedentary workers are higher or lower than average trends of the population, these differences arise mainly from various reasons such as the purpose of the survey, South Korean culture, regional characteristics and online survey property. Furthermore, since the purpose of the survey is to measure the modal shift effects of the MSP from car to PT, the characteristics of car possession and car use in South Korea seem to affect the participation of the survey significantly. Consequently, overall representativeness of samples can be acceptable. In addition, overviews of survey data and the results of frequency analysis are presented. In particular, the frequency analyses about the most effective and acceptable MSP are investigated. The result of the analysis indicates that improving the quality of PT service in the short term and improving PT facilities in the long term take the highest frequency ratio. In addition, the results of the survey show that priority for improving PT is faster services. This result can be used as significant information on transport policy in South Korea.

Chapter 5. Data Analysis Using Logit Models

5.1. Introduction

The purpose of this chapter is to calibrate appropriate models and predict the modal shift effect of MSP. This chapter is made up of six sections. Section 5.2 shows not only the estimation result of the standard logit model with only the alternative-specific variables, but also the prediction of modal shift effect of MSP. Section 5.3 compares modal shift effect of MSP at the same monetary level of policy intervention. Section 5.4 deals with marginal modal shift probability of MSP. Section 5.5 compares modal shift effects between a fixed sum scheme and fixed rate scheme concerning PT commuting cost subsidy policy. Section 5.6 develops the mixed logit models.

5.2. Estimation Result of Standard Logit Models with Only Alternative-Specific Variables

5.2.1. Review of the goodness of fit of models and coefficients

The R software was used to carry out the SP analysis; a total of 20,248 data points (missing data points 461 out of 20,709) was obtained from the 767 respondents, based on 27 questions. As shown in **Table 5-1**, many coefficients are statistically significant in terms of the absolute t-value, with all such values larger than 2.57 and, therefore, significant at the 99% level. That is, it means that many individual MSPs and the combined MSPs affect the choice of travel mode significantly. Although all the three-factor interaction coefficients (β_{123}) are statistically insignificant, most of the two-factor interaction coefficients, except for the β_{12} and the β_{13} in model C1, are statistically significant. Consequently, this result indicates that many 'two-factor interaction' variables is statistically significant and should be included in the utility specification. In addition, the ρ^2 values of models with interaction terms are higher than those of models without interaction terms even though these differences between the ρ^2s are all pretty marginal [e.g. model A2(0.286) > A0(0.282); B2(0.327) > B0(0.324); C2(0.280) > C0(0.278)]. Therefore, it indicates that models with interaction terms are more suitable for this research than models without interaction terms.

The sign of a coefficient indicates the commuter's preference for the choice of travel mode. That is, this sign shows the tendency of whether the utility of car users increases or decreases. The negative signs of the coefficients (β_2 and β_3) involving car users mean that there are reverse relationships between the levels of the MSPs and the utility of car users. If a level in one attribute (MSP) rises, the utility of car users will decrease. Therefore, the higher the level of each MSP, the lower the use of a car. In short, the implementation of the additional parking fees (β_2) or congestion charges (β_3) leads to the decrease in the utility of car users. On the other hand, the positive sign of the coefficient (β_1) associated with PT users means that there is an affirmative relationship between the level of the MSP and the utility of PT users. In short, PT commuting cost subsidies create the increase in the utility of PT users. All in all, all the signs of the coefficients are acceptable in common sense.

Meanwhile, the absolute values of coefficients illustrate the magnitude of modal shift effect of the MSPs in the utility function. In general, the bigger the absolute values of the coefficient, the greater the modal shift effect of attributes. Through the absolute values of the coefficients β_1, β_2 and β_3, the relative values of modal shift effect of the MSP can be understood. In addition, a positive sign of β_0 (ASC) implies an affirmative relationship between the β_0 and the utility of the car use since the β_0 is located on the utility of car use.

Table 5-1. Estimation results of the models with alternative-specific variables

Type of model	Coefficient	Beta	Value	t-value	Goodness of fit of the statistics
Model A0	**ASC**	$\boldsymbol{\beta_0}$	**0.3905**	**10.2937****	L(0) = - 14035.5
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.4868**	**22.3107****	L($\widehat{\beta}$)= - 10070.9
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.5328**	**-24.3243****	ρ^2 * = 0.282
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.6959**	**-31.1423****	Number of observations: 767
Model B0	ASC	β_0	0.0727	1.8804	L(0) = - 12405.3
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.1191**	**13.0699****	L($\widehat{\beta}$)= - 8389.1
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.2287**	**-23.4739****	ρ^2= 0.324
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.2461**	**-29.5910****	Number of observations: 678
Model C0	**ASC**	$\boldsymbol{\beta_0}$	**0.3006**	**7.3775****	L(0) = - 10704.3
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.1275**	**13.6759****	L($\widehat{\beta}$)= - 7723.2
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.2384**	**-23.7223****	ρ^2= 0.278
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.3135**	**-28.7722****	Number of observations: 582
Model A1	**ASC**	$\boldsymbol{\beta_0}$	**0.7778**	**13.1817****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.7645**	**-16.2370****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.8395**	**-17.6068****	L(0) = - 14035.5
	Congestion charge	$\boldsymbol{\beta_3}$	**-1.0356**	**-20.7312****	L($\widehat{\beta}$)= -10024.9
	Subsidy & Parking	$\boldsymbol{\beta_{12}}$	**0.1792**	**4.5676****	ρ^2= 0.286
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.2061**	**5.0023****	Number of observations: 767
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.2417**	**5.8252****	
	Subsidy & Parking & Congestion	β_{123}	-0.0643	-1.8552	
Model B1	**ASC**	$\boldsymbol{\beta_0}$	**0.3519**	**6.5041****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.2107**	**11.0104****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.3200**	**-17.4902****	L(0) = - 12405.3
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.3324**	**-20.6539****	L($\widehat{\beta}$)= - 8354.6
	Subsidy & Parking	$\boldsymbol{\beta_{12}}$	**0.0228**	**3.5452****	ρ^2= 0.327
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0227**	**4.0517****	Number of observations: 678
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0245**	**4.4748****	
	Subsidy & Parking & Congestion	β_{123}	-0.0016	-0.8997	

Model C1	**ASC**	β_0	**0.5645**	**9.8020****	
	PT commuting cost subsidy	β_1	**0.1984**	**10.2305****	
	Additional parking fee	β_2	**-0.3478**	**-18.2058****	L(0) = - 10704.3
	Congestion charge	β_3	**-0.4070**	**-19.0543****	L($\widehat{\beta}$)= - 7695.7
	Subsidy & Parking	β_{12}	**0.0276**	**4.3512****	ρ^2= 0.281
	Subsidy & Congestion	β_{13}	0.0150	1.9406	Number of observations: 582
	Parking & Congestion	β_{23}	**0.0385**	**5.3087****	
	Subsidy & Parking & Congestion	β_{123}	-0.0038	-1.4626	

Model A2	**ASC**	β_0	**0.7331**	**13.6720****	
	PT commuting cost subsidy	β_1	**0.7173**	**18.1306****	L(0) = - 14035.5
	Additional parking fee	β_2	**-0.7926**	**-19.8233****	L($\widehat{\beta}$)= - 10026.6
	Congestion charge	β_3	**-0.9845**	**-23.7696****	ρ^2= 0.286
	Subsidy & Parking	β_{12}	**0.1270**	**4.6482****	Number of observations: 767
	Subsidy & Congestion	β_{13}	**0.1494**	**5.3694****	
	Parking & Congestion	β_{23}	**0.1848**	**6.6217****	
Model B2	**ASC**	β_0	**0.3341**	**6.6694****	
	PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	L(0) = - 12405.3
	Additional parking fee	β_2	**-0.3121**	**-19.5858*****	L($\widehat{\beta}$)= - 8354.9
	Congestion charge	β_3	**-0.3253**	**-23.3928****	ρ^2= 0.327
	Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	Number of observations: 678
	Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	
	Parking & Congestion	β_{23}	**0.0213**	**5.0954****	
Model C2	**ASC**	β_0	**0.4212**	**9.0892****	L(0) = - 10704.3
	PT commuting cost subsidy	β_1	**0.1285**	**13.7311****	L($\widehat{\beta}$)= - 7707.8
	Additional parking fee	β_2	**-0.2928**	**-20.6365****	ρ^2= 0.280
	Congestion charge	β_3	**-0.3757**	**-23.6870****	Number of observations: 582
	Parking & Congestion	β_{23}	**0.0303**	**5.5603****	

After taking measures to exclude statistically insignificant coefficients (β_{13}, β_{123}) in model C1, a new model (model C2') has been developed. However, since the estimated model C2' includes also statistically insignificant coefficient (β_{12}). Therefore, after excluding statistically insignificant coefficients (β_{12}) in model C2', a new model (model C2) has been developed.

ModelC2'	**ASC**	β_0	**-0.4443**	**-8.9159****	
	PT commuting cost subsidy	β_1	**0.1398**	**10.7850****	L(0) = - 10704.3
	Additional parking fee	β_2	**0.2935**	**20.6413****	L($\widehat{\beta}$)= - 7707.0
	Congestion charge	β_3	**0.3883**	**20.7615****	ρ^2= 0.280
	Subsidy& Parking	β_{12}	-0.0067	-1.2852	Number of observations: 582
	Parking & Congestion	β_{23}	**-0.0306**	**-5.5976****	

* The estimation result is based on the separate utility functions such as the utility function of car users and the utility function of PT users. In addition, the integrated utility function of both car user and PT user can be also calibrated. In this case, the sign of PT commuting cost subsidy is just changed as a reverse sign. However, the estimated choice probability of travel mode by using the two types of utility functions are always equal.

* For example, the calculation of the ρ^2 in model A0: $\rho^{2*} = 1 - \frac{L(\widehat{\beta})}{L(0)} = 1 - \frac{-10070.9}{-14035.5} = 0.282469$

* The bold figures mean that the coefficient is statistically significant since t-value is larger than 1.96.

* Superscript ** represents significance within 1%.

5.2.2. Prediction of modal shift effects of modal shift policies

The utility values of a travel mode are calculated as in the following way. For example, in the case of model A2, the utility values of car use can be estimated as follows:

$$V_{car} = 0.7331 + (-0.7926)\cdot Park_j + (-0.9845)\cdot Congestion_j + (0.127)\cdot Subsidy_j\cdot Park_j + (0.1494)\cdot Subsidy_j\cdot Congestion_j + (0.1848)\cdot Park_j\cdot Congestion_j \quad (5\text{-}1)$$

To get the maximum utility of car use, the maximizing values of the MSP (β_2, β_3, β_{12}, β_{13}, β_{23}, *and* β_{123}) are substituted into the utility of car use as in **Equation 5-1**. In the case of model A2, the values of each level (0, 1 and 2) are put into **Equation 5-1**. The utility value of car use is simply calculated by the method of substitution. For example, under the condition 16 (input value: $Subsidy_j$: 1; $Park_j$: 2; $Congestion_j$: 0) the deterministic part of the utility of car use are calculated as follows:

$$V_{car} = 0.7331 + (-0.7926)\cdot(2) + (-0.9845)\cdot(0) + (0.127)\cdot(1)\cdot(2) + (0.1494)\cdot(1)\cdot(0) + (0.1848)\cdot(2)\cdot(0)$$
$$V_{car} = -0.5981, \qquad U_{car} = e^{-0.5981} = 0.549855 \quad (5\text{-}2)$$

The utility value of car usage is 0.549855.

Meanwhile, the utility of PT use in model A2 are calculated in the following way. To get the maximum utility of PT use, the maximizing values of the MSP (β_1: 0.7173) are substituted into the utility of PT use as in **Equation 5-3**.

$$V_{PT} = (0.7173)\cdot Subsidy_j = (0.7173)\cdot(1) = 0.7173, \qquad U_{PT} = e^{0.7173} = 2.048894 \quad (5\text{-}3)$$

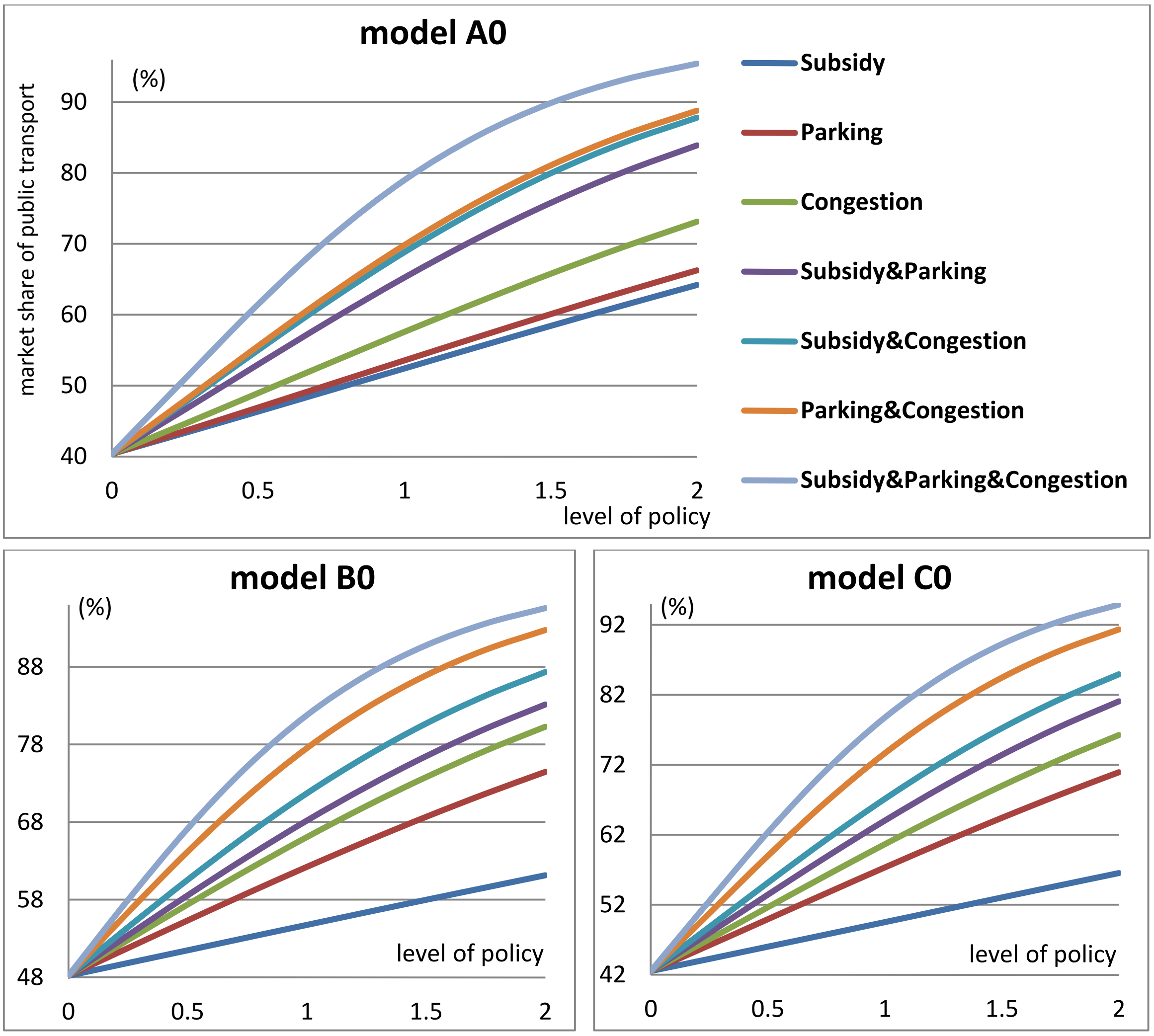
The utility value of PT use is 2.048894.

$$P^i_{car} = \frac{e^{V_{i,car}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{e^{(-0.5981)}}{e^{(-0.5981)} + e^{(0.7173)}} = 0.211585 \cong \mathbf{21.16}\% \quad (5\text{-}4)$$
$$P^i_{PT} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{e^{(0.7173)}}{e^{(-0.5981)} + e^{(0.7173)}} = 0.788415 \cong \mathbf{78.84}\ \% \quad (5\text{-}5)$$

From the utility function, the choice probability of the car use is 0.211585, whereas the choice probability of PT use is 0.788415. The other example and the detailed calculation process of the utility values and the choice probability of a travel mode are attached in **Appendix 2**.

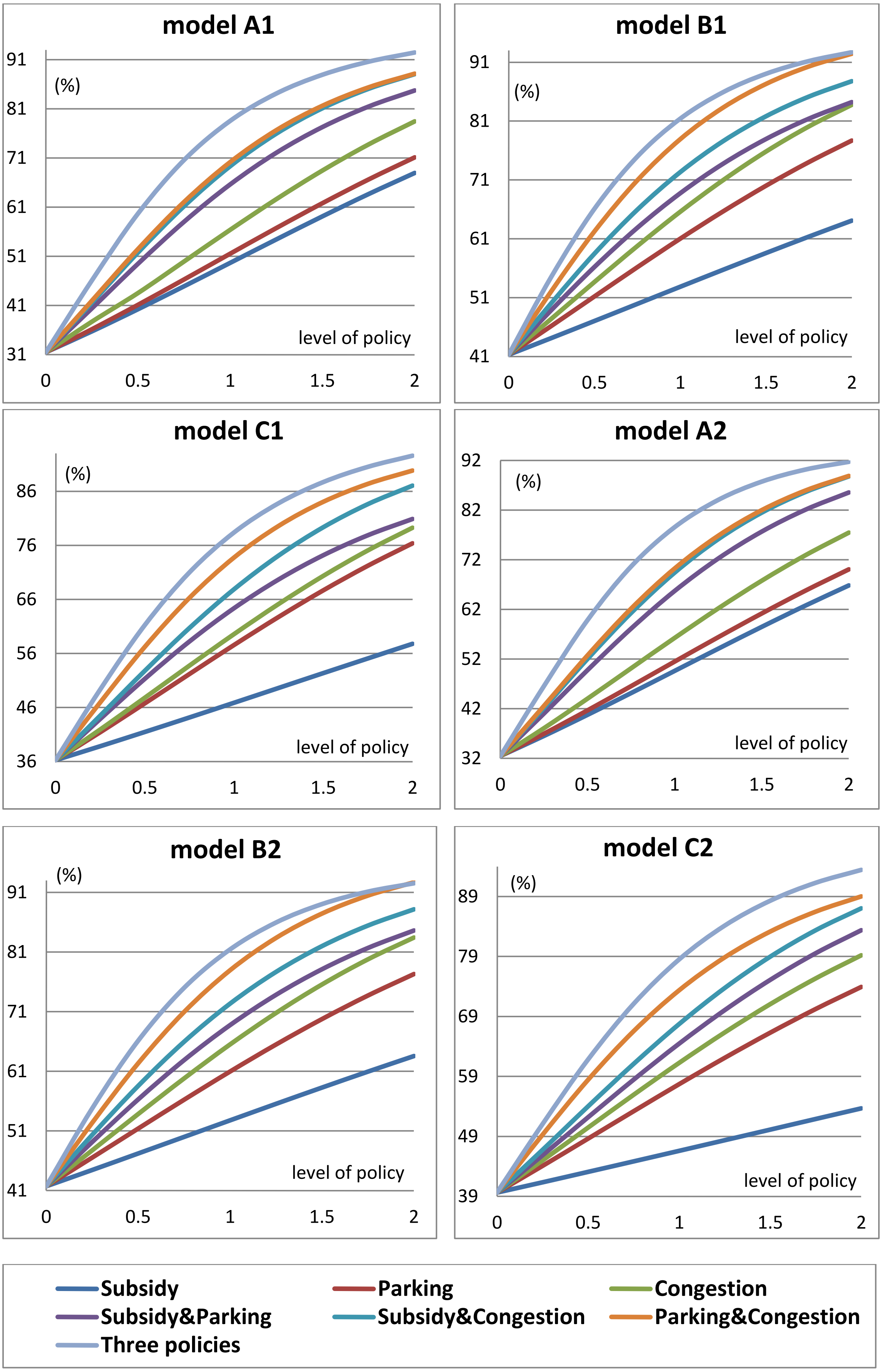
In addition, as indicated in **Figure 5-1**, the modal shift probabilities regarding MSP can be compared. If the modal shift probability (market share of PT) increases according to the rise in policy intervention, it can be judged that the MSP has a modal shift power. In terms of modal shift effects, the orders of modal shift effect of the MSP in all the types of models with only the alternative-specific variables are presented as follows: ① PT commuting cost subsidies & additional parking fees & congestion charges, ② additional parking fees & congestion charges, ③ PT commuting cost subsidies & congestion charges, ④ PT commuting cost subsidies & additional parking fees, ⑤ congestion charges, ⑥ additional parking fees, ⑦ PT commuting cost subsidies. Even though the modal shift effect of the MSP demonstrates only a small difference in the magnitude according to the different type of models, the order of modal shift effect remains the same result. According to **Figure 5-1**, even though the magnitude of the gaps between the curves varies, the order of modal shift effect remains consistent regardless of the type of models.

Figure 5-1. Comparison of the modal shift probability curve of the combined MSPs in models with only alternative-specific variables



* **Level 1**: 'subsidy' = mean **2,211** won, 'parking' = mean **2,500** won, 'congestion' = mean **3,000** won (when reflecting reduced travel time: mean **2,339** won), / 'subsidy + parking' = mean 4,711 won, 'subsidy + congestion' = mean 5,211 won (when reflecting reduced travel time: mean 4,550 won), 'parking + congestion' = mean 5,500 won (when reflecting reduced travel time: mean 4,839 won), 'subsidy + parking + congestion' = mean 7,711 won (when reflecting reduced travel time: mean 7,050 won)

* **Level 2**: 'subsidy' = mean **4,422** won, 'parking' = mean **5,000** won, 'congestion' = mean **6,000** won (when reflecting reduced travel time: mean **4,677** won) / 'subsidy + parking' = mean 9,422 won, 'subsidy + congestion' = mean 10,422 won (when reflecting reduced travel time: mean 9,099 won), 'parking + congestion' = mean 11,000 won (when reflecting reduced travel time: mean 10,677 won), 'subsidy + parking + congestion' = mean 15,422 won (when reflecting reduced travel time: mean 14,099 won)


model A1
(%)
91
81
71
61
51
41
31
0
0.5
1
1.5
2
level of policy
model B1
(%)
91
81
71
61
51
41
0
0.5
1
1.5
2
level of policy
model C1
(%)
86
76
66
56
46
36
0
0.5
1
1.5
2
level of policy
model A2
(%)
92
82
72
62
52
42
32
0
0.5
1
1.5
2
level of policy
model B2
(%)
91
81
71
61
51
41
0
0.5
1
1.5
2
level of policy
model C2
(%)
89
79
69
59
49
39
0
0.5
1
1.5
2
level of policy
Subsidy
Parking
Congestion
Subsidy&Parking
Subsidy&Congestion
Parking&Congestion
Three policies

5.3. Comparison of Modal Shift Effects at the Same Monetary Level of Policy Intervention

5.3.1. Necessity of comparison at the same monetary level of policy intervention

Since the values of the level of each alternative-specific variable (MSP) in the hypothetical condition of the SP survey have monetary differences, the previous analysis (**section 5.2.**) cannot be regarded as equal comparison under the same monetary level of policy intervention. In the example of models B, the level-one value of the PT commuting cost subsidy is 2,211 won (£1.23), additional parking fee 2,500 won (£1.39), and the congestion charge 3,000 won (£1.67). Consequently, true values of the level of each MSP are different respectively. In addition, the previous prediction (see **section 5.2.**) for the combined MSPs must be exaggerated because the true input values of the combined MSPs are double or triple as those of a single MSP in the calculation of utility value. Therefore, to accurately understand the modal shift effects of the combined MSPs, the equal condition should be constructed. That is, comparison of an individual MSP and the combined MSPs under the same monetary level of policy intervention is needed.

To create the equal condition, it is assumed that the policy intervention of the combined MSPs is equally distributed into each MSP. For example, suppose the maximum limitation of budget or levy is 2,000 won (£1.11). In the case of the implementation of two combined MSPs, each MSP will be assigned by 1,000 won (£0.56, = 2,000 won × (1/2)) as an input magnitude of policy intervention. That is, the input value for each MSP is 1,000 won, not 2,000 won. In addition, in the case of three combined MSPs, an individual MSP will be allocated by 666.6 won (£0.37, = 2,000 won × (1/3)). That is, the input value for every MSP is 666.6 won, not 2,000 won.

The calculation process of the utility value and the choice probability of the travel mode at the same monetary level of policy intervention are attached in **Appendix 3**. **Table 5-2** compares market share rate of PT in respect to MSPs under the same monetary level of economic policy intervention. The order of the modal shift effect of the MSP is similar to that of **Section 5.2**. However, there are some exceptions. In the case of the individual MSP, models A, which is a model using only the SP data (level data), show that modal shift effects of PT commuting cost subsidies are higher than additional parking fees (see blue figures in **Table 5-2**). In addition, model C1, which is a model including statistically insignificant coefficients, represents that the greatest level of modal shift would be achieved by the introduction of additional parking fees (see bold figures in **Table 5-2**).

Table 5-2. Comparison of the market share rate of PT in respect to MSPs at the same monetary level of policy intervention (unit: %)

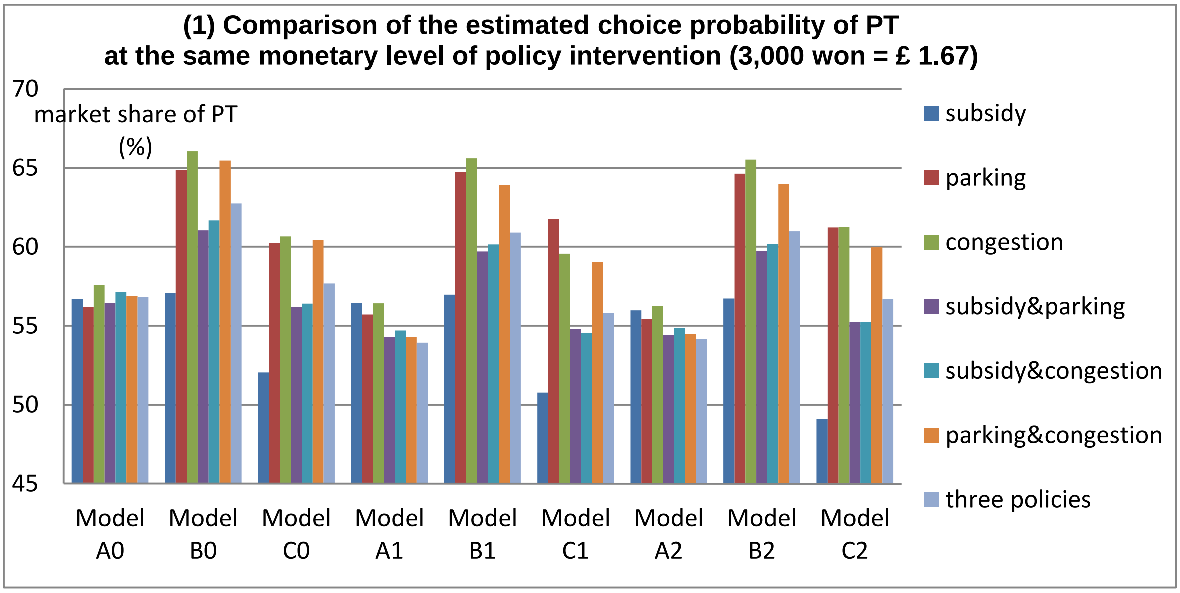
Policy intervention	Type of Model	Present (0 won)	Subsidy	Parking	Congestion charge	Subsidy& Parking	Subsidy& Congestion	Parking& Congestion	Subsidy& Parking& Congestion
1,000 won (£ 0.56)	Model A0	40.36	45.75 (13.35)	45.58 (12.93)	**46.04 (14.07)**	45.66 (13.13)	45.9 (13.73)	45.81 (13.50)	45.79 (13.45)
	Model B0	48.18	51.16 (6.19)	53.89 (11.85)	**54.32 (12.74)**	52.53 (9.03)	52.74 (9.46)	54.11 (12.31)	53.13 (10.27)
	Model C0	42.54	45.68 (7.38)	48.45 (13.89)	**48.6 (14.25)**	47.06 (10.63)	47.14 (10.81)	48.52 (14.06)	47.57 (11.82)
	Model A1	31.48	**39.36 (25.03)**	39.13 (24.30)	39.35 (25.00)	39.05 (24.05)	39.17 (24.43)	39.05 (24.05)	39.03 (23.98)
	Model B1	41.29	46.68 (13.05)	49.2 (19.16)	**49.51 (19.91)**	47.7 (15.52)	47.85 (15.89)	49.2 (19.16)	48.2 (16.74)
	Model C1	36.25	40.95 (12.97)	**44.6 (23.03)**	43.85 (20.97)	42.6 (17.52)	42.32 (16.74)	44.04 (21.49)	42.94 (18.46)
	Model A2	32.45	39.92 (23.02)	39.75 (22.50)	**40.01 (23.30)**	39.7 (22.34)	39.83 (22.74)	39.73 (22.43)	39.71 (22.37)
	Model B2	41.72	46.69 (11.91)	49.45 (18.53)	**49.78 (19.32)**	47.95 (14.93)	48.12 (15.34)	49.48 (18.60)	48.48 (16.20)
	Model C2	39.62	42.73 (7.85)	46.79 (18.10)	**46.8 (18.12)**	44.76 (12.97)	44.76 (12.97)	46.65 (17.74)	45.37 (14.51)
3,000 won (£ 1.67)	Model A0	40.36	56.70 (40.49)	56.19 (39.22)	**57.58 (42.67)**	56.45 (39.87)	57.14 (41.58)	56.88 (40.93)	56.82 (40.78)
	Model B0	48.18	57.07 (18.45)	64.87 (34.64)	**66.05 (37.09)**	61.04 (26.69)	61.66 (27.98)	65.46 (35.87)	62.74 (30.22)
	Model C0	42.54	52.05 (22.36)	60.22 (41.56)	**60.65 (42.57)**	56.17 (32.04)	56.40 (32.58)	60.44 (42.08)	57.68 (35.59)
	Model A1	31.48	**56.44 (79.29)**	55.71 (76.97)	56.41 (79.19)	54.27 (72.40)	54.70 (73.76)	54.27 (72.40)	53.92 (71.28)
	Model B1	41.29	56.96 (37.95)	64.75 (56.82)	**65.60 (58.88)**	59.70 (44.59)	60.15 (45.68)	63.91 (54.78)	60.89 (47.47)
	Model C1	36.25	50.77 (40.06)	**61.75 (70.34)**	59.57 (64.33)	54.80 (51.17)	54.56 (50.51)	59.04 (62.87)	55.79 (53.90)
	Model A2	32.45	55.96 (72.45)	55.43 (70.82)	**56.25 (73.34)**	54.42 (67.70)	54.86 (69.06)	54.47 (67.86)	54.15 (66.87)
	Model B2	41.72	56.72 (35.95)	64.62 (54.89)	**65.52 (57.05)**	59.74 (43.19)	60.19 (44.27)	63.97 (53.33)	60.97 (46.14)
	Model C2	39.62	49.11 (23.95)	61.23 (54.54)	**61.25 (54.59)**	55.25 (39.45)	55.26 (39.48)	59.97 (51.36)	56.70 (43.11)
6,000 won (£ 3.33)	Model A0	40.36	71.71 (77.68)	70.85 (75.55)	**73.13 (81.19)**	71.28 (76.61)	72.42 (79.44)	72.01 (78.42)	71.91 (78.17)
	Model B0	48.18	65.52 (35.99)	78.58 (63.10)	**80.28 (66.63)**	72.53 (50.54)	73.55 (52.66)	79.44 (64.88)	75.31 (56.31)
	Model C0	42.54	61.41 (44.36)	75.58 (77.67)	**76.24 (79.22)**	68.94 (62.06)	69.32 (62.95)	75.91 (78.44)	71.51 (68.10)
	Model A1	31.48	**78.51 (149.40)**	77.50 (146.19)	78.47 (149.27)	72.61 (130.65)	73.40 (133.16)	72.61 (130.65)	71.58 (127.38)
	Model B1	41.29	71.35 (72.80)	82.75 (100.41)	**83.79 (102.93)**	73.79 (78.71)	74.52 (80.48)	79.98 (93.70)	75.16 (82.03)
	Model C1	36.25	65.16 (79.75)	**82.09 (126.46)**	79.24 (118.59)	69.54 (91.83)	70.63 (94.84)	76.15 (110.07)	71.28 (96.63)
	Model A2	32.45	77.08 (137.53)	76.30 (135.13)	**77.48 (138.77)**	72.79 ② (124.31)	73.53 ① (126.59)	72.73 ③ (124.13)	71.61 120.68
	Model B2	41.72	70.58 (69.18)	82.32 (97.32)	**83.45 (100.02)**	73.87 ③ (77.06)	74.58 ② (78.76)	80.00 ① (91.75)	75.18 (80.20)
	Model C2	39.62	58.66 (48.06)	79.18 (99.85)	**79.19 (99.87)**	69.90 ③ (76.43)	69.91 ② (76.45)	75.46 ① (90.46)	71.36 (80.11)

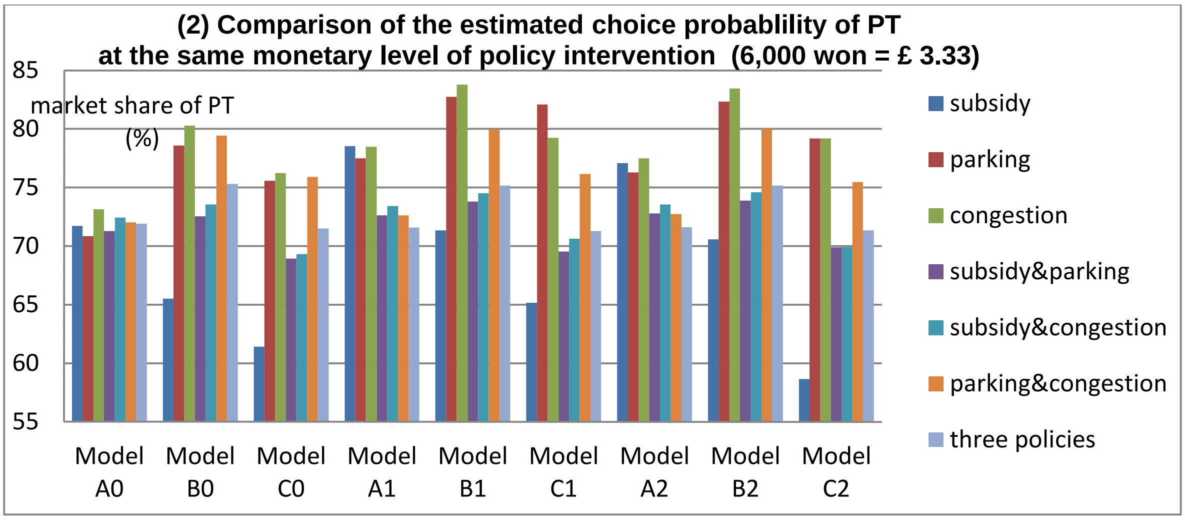
* The values in parenthesis ( ) mean the change rate of modal shift from car to PT according to the change of level of MSP based on the current state.
$\left(\frac{\textit{market share of the PT after the implementation of the MSP}\ \%}{\textit{market share of the PT before the impelemtatin of the MSP}\ \%} - 1\right) \text{ X } 100\%$
* The highest value in individual MSP and combined MSPs is highlighted.
* The blue coloured letter means that the order of modal shift probability is different from the general order of modal shift probability (i.e. PT subsidy < parking fee < congestion charge).
* The orange coloured block offers the comparison of modal shift effect of the three combined MSPs (instance for **section 6.4.5**)

5.3.2. Review of models A

Figure 5-2 compares the estimated choice probability (market share) of PT at the same monetary level of policy intervention. Modal shift effects of congestion charges are the strongest (see models A in **Table 5-2** and **Figure 5-2**). In addition, an interesting the point is that the modal shift effects of PT commuting cost subsidies in models A, which are based on the level unit, are more significant than those of additional parking fees. Model A0, a model without interaction terms, shows that modal shift effects of congestion charges are more than those of PT commuting cost subsidies. However, in model A1, a model with interaction terms including statistically insignificant, the modal shift effects of congestion charges are less than those of PT commuting cost subsidies. This result is very different from the modal shift effect of other models. However, since model A1 is a model including statistically insignificant coefficients, there is a limitation of providing big significance in terms of statistics. That is, model A2, a model with interaction terms comprised of only statistically significant variables, shows that the modal shift effects of congestion charges are a little superior to PT commuting cost subsidies.

Figure 5-2. Comparison of the estimated choice probability of PT at the same monetary level of policy intervention





Meanwhile, in model A0, without interaction terms, the modal shift effects of the combined MSPs are placed between two individual MSP whereas in model A1 and A2, with interaction terms, the modal shift effects of the combined MSPs are inferior to those of the individual MSP. In addition, a remarkable indication is that models of using only the SP data (i.e. models A) show that pull measures (e.g. subsidy) are more effective than push measures (e.g. additional parking fee).

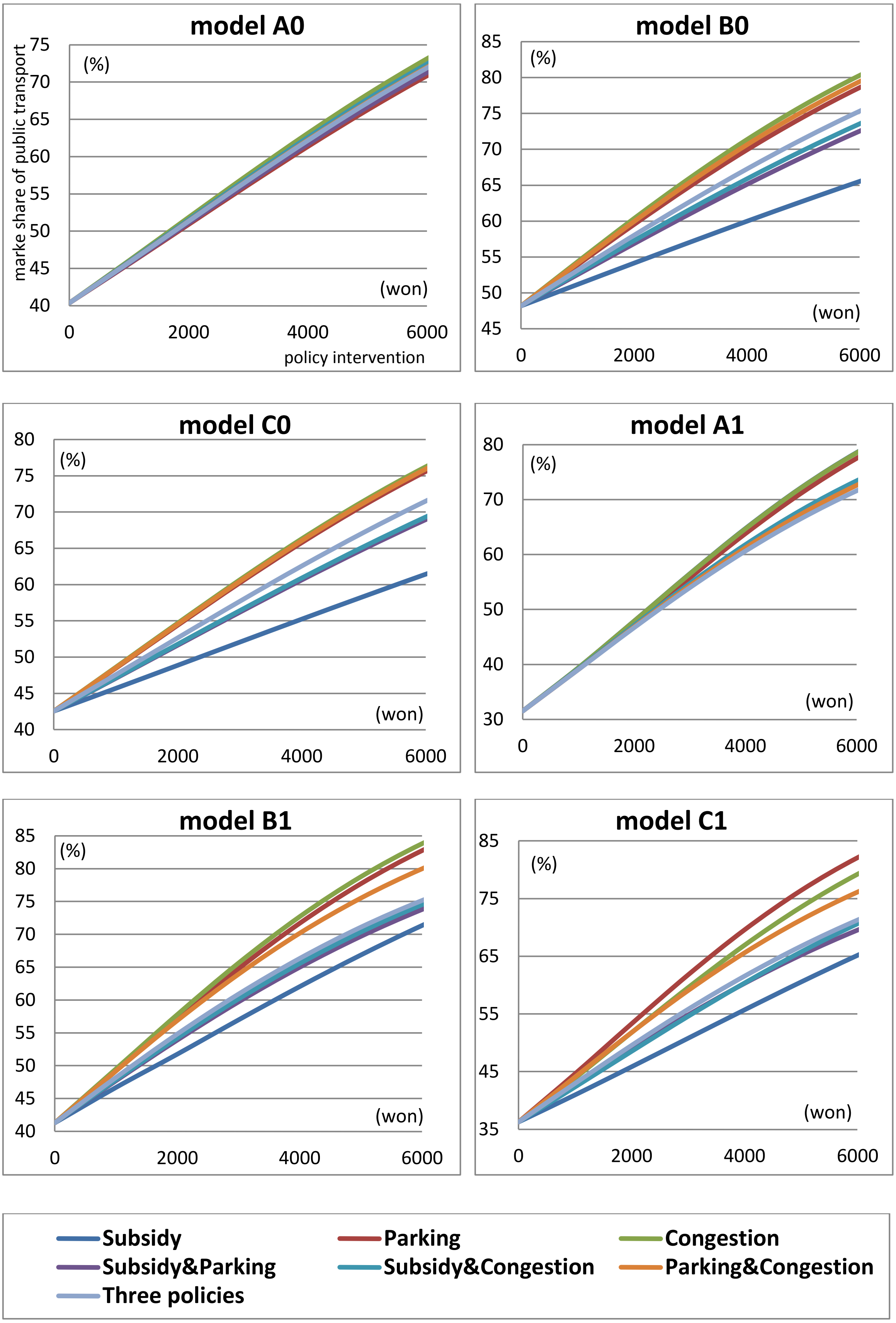
5.3.3. Review of models B

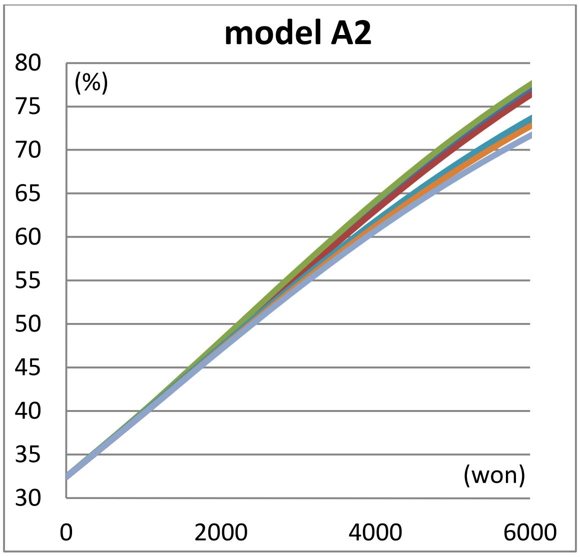
The reflection of the individual's PT commuting costs (e.g. level one : mean 2,211 won, level two : mean 4,422 won), instead of the reflection of the level values of PT commuting cost subsidies (e.g. level 0, 1, and 2), allows to modify or transform level-based models into money-based models. The unit of the MSP is changed from the level unit into the monetary unit in models B. In models B, the modal shift effects of PT commuting cost subsidies are very much lower than the other MSP.

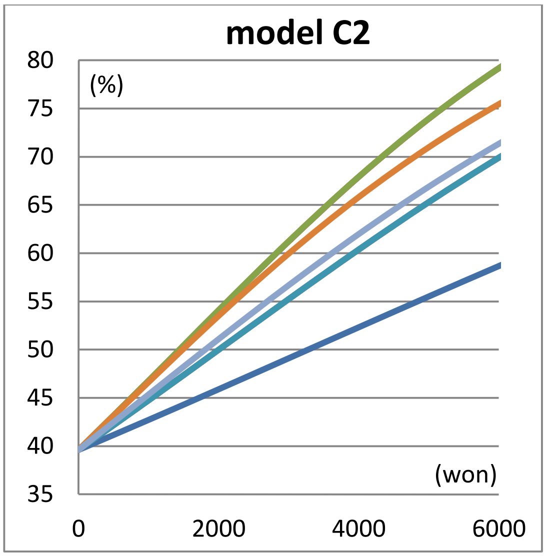
5.3.4. Review of models C

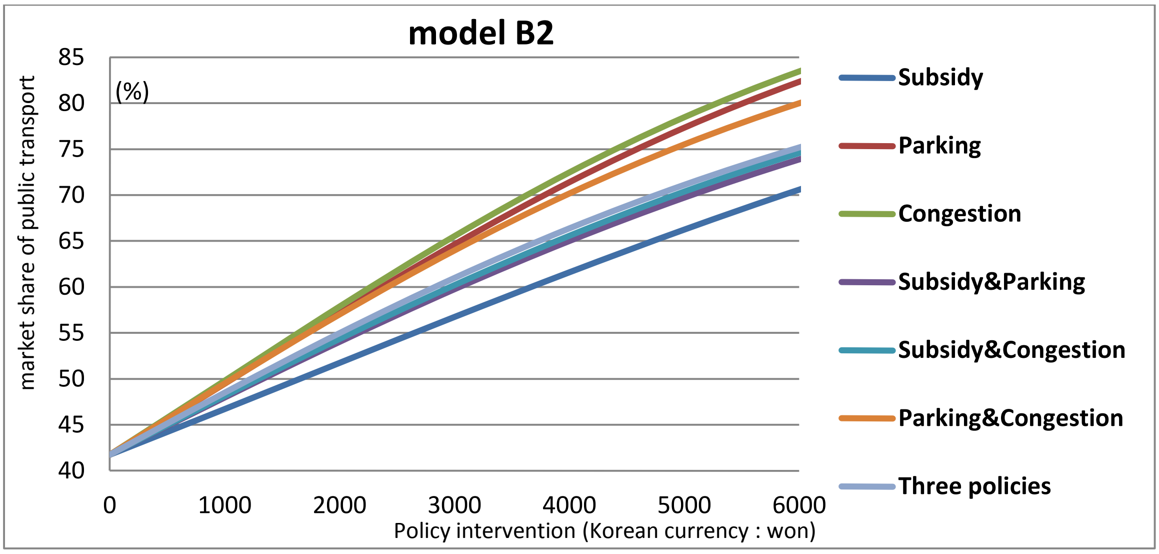
Models C, reflect not only individual's the PT commuting cost but also individuals' reductions in commuting time in regard to congestion charges, show clearly the modal shift effect of the MSP. Model C0, a model without interaction terms, shows that the modal shift effects of congestion charges are higher than additional parking fees. However, in the case of model C1, the modal shift effects of congestion charges are less than additional parking fees. This result is very different from the modal shift effects of other models. However, since model C1 is a model including statistically insignificant coefficients, it cannot be accepted in terms of statistics. Meanwhile, model C2, a model with interaction terms comprising only statistically significant variables, shows that modal shift effects of congestion charges are almost equal or higher than additional parking fees.

Figure 5-3. Comparison of the modal shift probability in respect to MSPs at the same monetary level of policy intervention









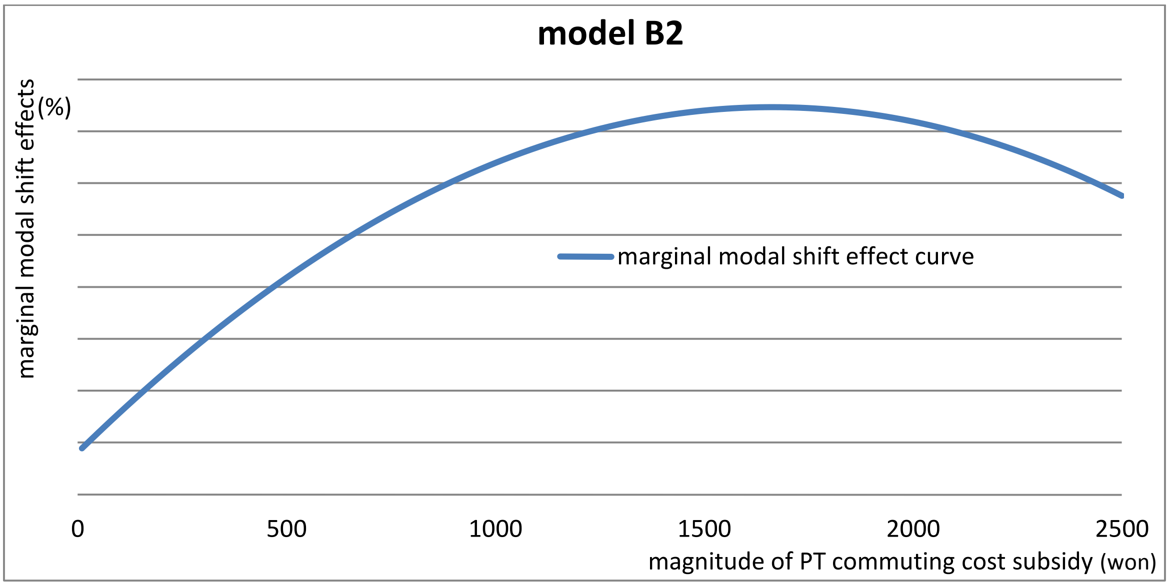
5.3.5. Review of all the models at the same monetary level of policy intervention

As shown in **Figure 5-2** and **Figure 5-3**, in most models, the most powerful modal shift effect of the individual MSP is obtained by the introduction of congestion charges while the lowest level of modal shift generated by PT commuting cost subsidies. However, in models A, the modal shift effects of PT commuting cost subsidies are higher than additional parking fees. Furthermore, in model A1, the modal shift effects of PT commuting cost subsidies are higher than congestion charges. In addition, in model C1, the modal shift effects of additional parking fees are higher than those of congestion charges. However, since model A1 and model C1 are models having statistically insignificant coefficients, these results are insignificant in terms of statistics. As a result, congestion charges may be the most cost-effective solution at the same monetary level of policy intervention.

5.4. Marginal Modal Shift Probability

The extra increase of market share of PT arising from the additional input of policy intervention (MSP) can be defined as marginal modal shift probability. As shown in **Figure 5-4**, at the initial stage the extra input of one unit of policy intervention can create greater modal shift probability than the previous extra input of one unit of policy intervention. It can be inferred that the introductory impact of the MSPs can influence the choices of a transport mode strongly. After reaching the maximum point of marginal modal shift effects, the extra input of one unit of policy intervention does not increase modal shift probability as much as the one before. At this stage, the law of diminishing marginal utility is applied. In economics, as the consumption of a certain good goes up, the marginal utility tends to be decreased. Similar to the case of goods, after the maximum point of marginal modal shift probability, modal shift probabilities of extra input of an additional unit of policy intervention are declined. In this case, the maximum point of marginal modal shift probability means the point that gains the highest modal shift probability by inputting the minimum policy intervention. Therefore, until the maximum point of marginal modal shift probability, the increase of policy intervention is more reasonable because the extra input of an additional unit of policy intervention can still create the increase in marginal modal shift probability.

Figure 5-4. The marginal modal shift probability curve of PT commuting cost subsidy in model B2



* Marginal modal shift probability = $\frac{\textit{market share rates of the PT at the particular policy intervention}}{\textit{market share rate of the PT at the previous policy intervention}}$*100 –100

* Y axis values do not exist because it depends on the magnitude of the divided unit. Therefore, the calculation of the maximum point on the X axis is focused.

Table 5-3 shows the degree of the policy intervention of obtaining maximum marginal modal shift probability. For example, in the case of the PT commuting cost subsidies, the average value of the policy intervention of obtaining maximum marginal modal shift probability is 1,981 won (£ 1.1).

Therefore, until the maximum point of marginal modal shift probability (1,981 won), the policy intervention should be increased in order to get more efficiency of the modal shift effects in the implementation of the PT commuting cost subsidies.

Table 5-3. Degree of the policy intervention (MSP) of obtaining the maximum marginal modal shift probability (unit: won)

MSP / Model	PT commute cost subsidy	Additional parking fee	Congestion charge	Subsidy & parking	Subsidy & Congestion	Parking & Congestion	Three policies
A0	1,780	1,840	1,690	1,810	1,730	1,760	1,765
B0	615	320	300	420	405	310	375
C0	2,360	1,265	1,235	1,650	1620	1,250	1,485
A1	2,255	2,325	2,255	1,385	1,435	1,395	1,130
B1	1,675	1,105	1,065	90	145	355	0
C1	2,850	1,625	1,785	620	1,500	830	615
A2	2,265	2,320	2,235	1,550	1,565	1,490	1,255
B2	1,665	1,075	1,035	185	220	380	0
C2	2,360	1,440	1,445	2,005	2,005	460	970
Average	1,981	**1,479**	1,449	**1,079**	1,181	914	844

As shown in **Table 5-3**, the average maximum points of policy intervention to marginal modal shift probabilities of a single MSP (e.g. 1,981 won in PT commuting cost subsidies, 1,479 won in additional parking fees) are higher than those of the combined MSPs (e.g. 1,079 won in a combination of PT commuting cost subsidies and additional parking fees). It can be interpreted that a larger amount of policy intervention for a single MSP is needed rather than the combined MSPs to get higher marginal modal shift probability.

In the same way as budget constraints occur in economics, policy intervention constraints may also exist. In general, policy intervention constraints may depend on complex factors such as the acceptability of the public, the severity of congestion, government's ability of finance and so on.

5.5. Comparison of Modal Shift Effects between a Fixed Sum Scheme and a Fixed Rate Scheme with Regard to Public Transport Commuting Cost Subsidy Policy

As stated earlier, models A are based on a relative unit of the level of support while models B are based on the absolute level of money. Models A are based the percentage of a PT commuting cost subsidy (e.g. 0% of the PT commuting cost, 50%, 100%) whereas models B are based on the monetary cost of a PT commuting subsidy (e.g. 0 won, 2,211 won, and 4,422 won). Thus, the two types of models can be compared to understand the modal shift effect of the different support schemes. Thus, the market share of a travel mode in 'a fixed rate scheme for the PT commuting cost subsidy' can be compared with that of 'a fixed sum scheme for the PT commuting cost subsidy' at the same standard (see **Table 5-4**). In this case, 'the fixed rate scheme for the PT commuting cost subsidy' is the way of providing commute cost subsidy for PT users as a form of fixed rate such as 0%, 50%, and 100% whereas 'the fixed sum scheme for the PT commuting cost subsidy' is the way of providing commute cost subsidy for PT users as a form of fixed sum such as 0 won, 2,211 won, and 4,424 won.

Table 5-4. Comparison of the fixed rate scheme and the fixed sum scheme with regard to PT commuting cost subsidy policy

Level	Support rate (%)	Support sum (won)	Market share of public transport (%)					
			Model A0	Model B0	Model A1	Model B1	Model A2	Model B2
0	0	0	40.36	48.18	31.48	41.29	32.45	41.72
0.25	12.5	553 (£0.31)	43.32	49.83	35.74	44.14	36.5	44.45
0.5	25	1,106 (£0.61)	46.33	51.47	40.24	47.03	40.75	47.22
0.75	37.5	1,658 (£0.92)	49.37	53.12	44.91	49.94	45.14	50
1	50	2,211 (£1.23)	52.41	54.75	49.67	52.85	49.61	52.78
1.25	62.5	2,764(£1.54)	55.43	56.38	54.43	55.74	54.08	55.55
1.5	75	3,317(£1.84)	58.41	57.99	59.12	58.59	58.49	58.28
1.75	87.5	3,869(£2.15)	61.33	59.58	63.65	61.38	62.77	60.96
2	100	4,422(£2.46)	64.18	61.16	67.94	64.1	66.85	63.57

* Model A0, A1, and A2: **the fixed rate scheme for the PT commute cost subsidy policy**
* Model B0, B1, and B2: the fixed sum scheme for the PT commute cost subsidy policy

From the self-reported survey data, the fact that the average value of a PT commuting cost from home to work is 2,211 won (£ 1.23) can be obtained. 2,211 won in the fixed sum scheme corresponds to 50% of a PT commuting cost subsidy in the fixed rate scheme, which implies the level one of 'a PT commuting cost subsidy' attribute in the survey. In addition, 4,422 won (£ 2.46) in the fixed sum scheme is equivalent to 100% of the PT commuting cost subsidy in the fixed rate scheme, which means the level two in the survey. As shown in **Table 5-4**, the market share of PT (i.e. the modal shift probability) at the same level of policy intervention can be compared.

Figure 5-5. Comparison of a fixed sum scheme with a fixed rate scheme

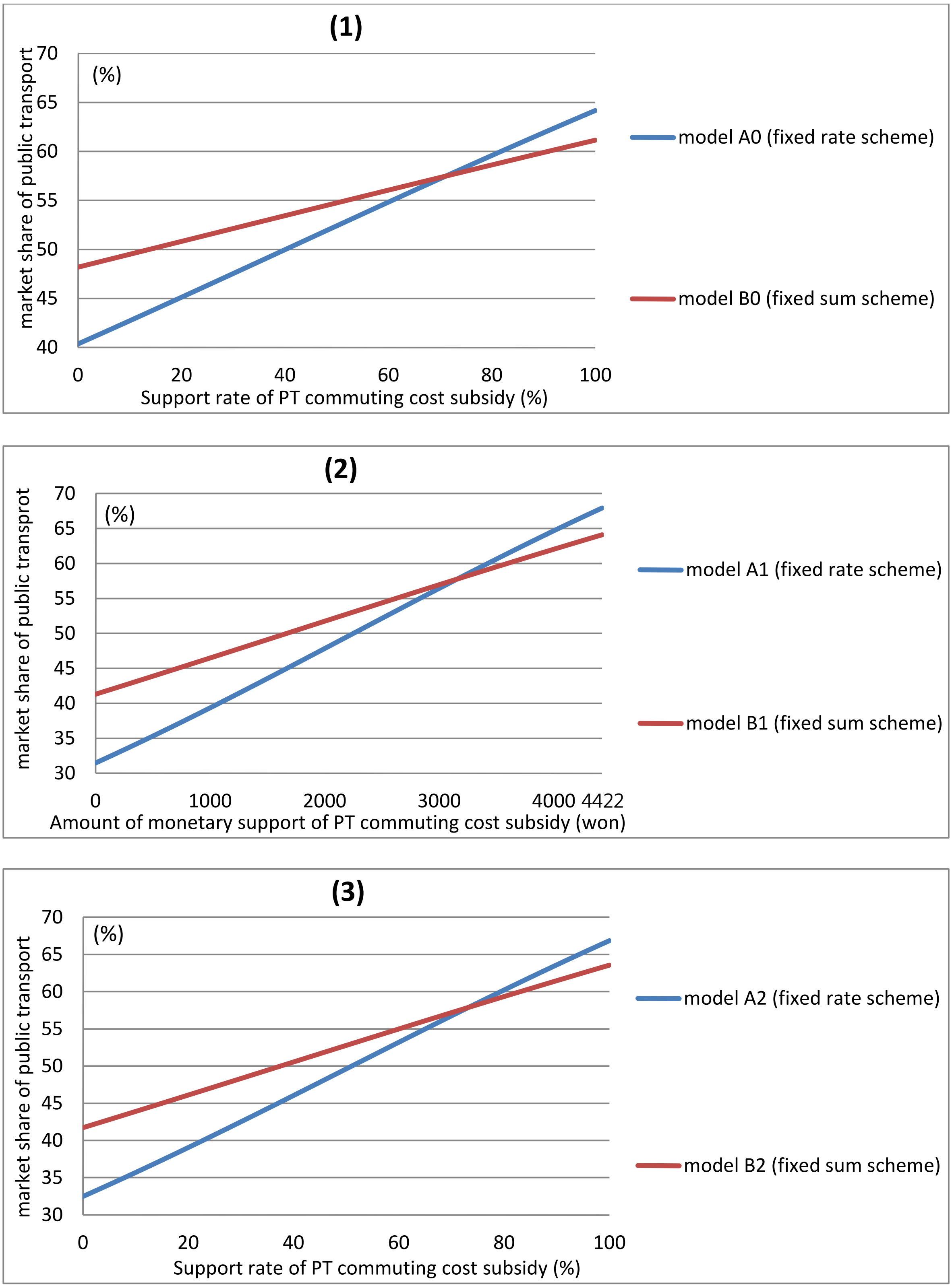


Figure 5-5 shows the market share of PT in models A with the fixed rate scheme and models B with the fixed sum scheme. Since the intercept and the slope of each model are different, the characteristics of each model can be understood. The intercept of the curves related to the fixed rate scheme (i.e. model A0, A1 and A2) is lower than that of the curves relevant to the fixed sum scheme (i.e. model

B0, B1 and B2). In addition, the slope of curves related to the fixed rate scheme is steeper than curves relevant to the fixed sum scheme. As shown in **Figure 5-5**, models A are more sensitive to the change of the amount of policy intervention than models B. Since the commuting fare of PT in South Korea is cheap relatively, many Korean workers may feel that the benefits from the fixed rate scheme are greater than the fixed sum scheme from a psychological perspective.

Comparing the shape of the graphs, it seems that in terms of the modal shift effects, the fixed sum scheme is more effective than the fixed rate scheme at the lower level of policy intervention (support). In **Figure 5-5**, before around 72% of the PT commuting cost subsidy (average value comes from the three contact points) or about 3,184 won (£ 1.77) per day, the graphs related to the fixed sum scheme are higher than the graphs associated with the fixed rate scheme. That is, at the stage of the lower support, the market share of PT in the fixed sum scheme is higher than that of the fixed rate scheme. After that, the graphs related to the fixed rate scheme are higher than the ones involving the fixed sum scheme. After turning points, it can be interpreted that in terms of modal shift effects, the fixed rate scheme is more effective than the fixed sum scheme. That is, at the stage of higher support, the market share of PT in the fixed rate scheme is higher than that of the fixed sum scheme. The modal shift probability curves indicate that if the amount of subsidy budget is limited to a lower level, the fixed sum scheme is more effective than the fixed rate scheme. However, the exact turning point depends on the type of models. (see **Table 5-5**).

Table 5-5. Contact points between the fixed rate scheme model and the fixed sum scheme model

Classification	Model B0	Model B1	Model B2
Model A0	3,140 won (1.42 level, 71%)	-	-
Model A1	-	3,162 won (1.43 level, 71.5%)	-
Model A2	-	-	3,250 won (1.47 level, 73.5%)

* Equation seeking for points of contact: $\frac{1}{1+1/exp(\beta_{0,r} + \beta_{1,r} \cdot PSubsidy)} = \frac{1}{1+1/exp(\beta_{0,s} + \beta_{1,s} \cdot PSubsidy)}$

$r \neq s$, r = {A0, A1, A2}, s = { B0, B1, B2}

In general, the fixed sum scheme can be a simpler and easier scheme in terms of public administration since the complicated calculation of support rate for individuals is not needed. Therefore, the fixed sum scheme may be preferable at the initial stage of introduction of the new MSP. This result indicates that the fixed sum scheme is more suitable for the payment scheme of grants at the lower level of governmental support, whereas the fixed rate scheme is more effective at the higher level of governmental support. This result may have significant implications for public administrators.

5.6. Estimation Result of Mixed Logit Models with Alternative-Specific Variables

To allow for preference heterogeneity among individuals, random coefficient models are calibrated. The R software (m-logit package) is used to carry out the SP analysis (Viton, 2014). As indicated in **Table 5-6**, the rho-squared index (ρ^2) values of the MLM are higher than those of standard logit models. The higher ρ^2 of the MLM means that the explanatory power of the MLM is greater than the standard logit model (Revelt and Train, 1998; Train, 1998). This result corresponds to the previous research (Bhat, 1998; Revelt and Train, 1998; Bhat, 2000; Amador et al., 2005; Yannis and Antoniou, 2007).

Table 5-6. Comparison of rho-squared index between the standard logit models and the mixed logti models, comprising alternative-specific variables, with the distribution of both normal and uniform

Classification	Model A0	Model B0	Model C0	Model A1	Model B1	Model C1	Model A2	Model B2	Model C2
Standard logit	0.282	0.324	0.278	0.286	0.327	0.281	0.286	0.327	0.280
Mixed logit (normal distribution)	0.284	0.335	0.292	0.286	0.336	0.295	0.286	0.336	0.295
Mixed logit (uniform distribution)	0.284	0.336	0.294	0.286	0.336	0.295	0.286	0.336	0.294

In a comparison of the estimated means in **Table 5-1** and **Table 5-7**, the MLM is higher than the standard logit models in most cases. The absolute values of the estimated coefficients of the MLM are greater than those of the standard logit models. It shows that the MLM is significantly higher sensitivity to the level of policy intervention. This result corresponds to the previous study (Bhat, 1998; Revelt and Train, 1998; Brownston and Train, 1999; Bhat, 2000; Brownstone et al., 2000; Whelan, 2003; and Yannis and Antoniou, 2007). This is mainly because the increasing portion of the coefficients, including the standard deviation of random coefficients, in the MLM comes from a portion of the utility belonging to unobserved stochastic terms in the standard logit model. Therefore, it can be inferred that the variance values of stochastic terms in the standard logit model are higher than those of the MLM (Revelt and Train, 1998).

All the coefficients of the main effects of the MSP are statistically significant in terms of the t-value, with all such absolute values larger than 2.57 and therefore significant at the 99% level (see **Table 5-7**). It means that these coefficients have a statistically significant preference of heterogeneity. That is, since the estimated standard deviation coefficients are highly significant, the coefficients vary in the population. However, in the models with interaction terms, most of the standard deviation coefficients (random effect coefficients) related to the interaction effect variables are statistically insignificant since the absolute t-value is less than 1.65. Furthermore, many of standard deviations related to main effect variables are statistically insignificant. In this case, since standard deviations represent all sources of preference heterogeneity, it can be interpreted that there is an absence of preference heterogeneity around the mean (Hensher et al., 2005). In particular, many means associated with interaction variables are statistically insignificant. It seems to imply that there is a limitation on the inclusion of the interaction effect of the MSP in the specification of the MLM.

Table 5-7. Estimation results of the mixed logit models with normal distribution

Type of model	Coefficient	Beta	Value	t-value	Goodness of fit of the statistics
Model A0	ASC	β_0	0.7683	11.2896**	L(0) = - 14035.5 L(β) = - 10044 ρ^2 = 0.284 Number of observations: 767
	PT commuting cost subsidy (Mean)	β_1	-0.8029	-11.3520**	
	Random effect (SD)		0.7521	5.9349**	
	Additional parking fee (Mean)	β_2	-0.9043	-12.0274**	
	Random effect (SD)		0.8334	6.8120**	
	Congestion charge (Mean)	β_3	-1.1013	-13.4137**	
	Random effect (SD)		0.7606	6.2012**	
Model B0	ASC	β_0	0.6662	9.5374**	L(0) = - 12405.3 L(β) = - 8244.7 ρ^2 = 0.335 Number of observations: 678
	PT commuting cost subsidy (Mean)	β_1	-0.5146	-11.3556**	
	Random effect (SD)		0.5492	9.6898**	
	Additional parking fee (Mean)	β_2	-0.3879	-11.3993**	
	Random effect (SD)		0.3142	5.9875**	
	Congestion charge (Mean)	β_3	-0.3824	-12.5058**	
	Random effect (SD)		0.2192	4.7309**	
Model C0	ASC	β_0	0.9518	12.2305**	L(0) = - 10704.3 L(β) = - 7578.6 ρ^2 = 0.292 Number of observations: 582
	PT commuting cost subsidy (Mean)	β_1	-0.4669	-11.7322**	
	Random effect (SD)		0.4764	9.2754**	
	Additional parking fee (Mean)	β_2	-0.4211	-12.3847**	
	Random effect (SD)		0.3815	7.6998**	
	Congestion charge (Mean)	β_3	-0.4484	-13.2196**	
	Random effect (SD)		0.1446	1.9423	
Model A1	ASC	β_0	0.7827	12.4295**	L(0) = - 14035.5 L(β) = - 10021 ρ^2 = 0.286 Number of observations: 767
	PT commuting cost subsidy (Mean)	β_1	-0.7726	-13.2304**	
	Random effect (SD)		-0.1375	-0.4173	
	Additional parking fee (Mean)	β_2	-0.8256	-14.9958**	
	Random effect (SD)		0.0551	0.1024	
	Congestion charge (Mean)	β_3	-1.0269	-15.3292**	
	Random effect (SD)		0.1197	0.3682	
	Subsidy & Parking (Mean)	β_{12}	0.1780	4.1453**	
	Random effect (SD)		0.0068	0.0172	
	Subsidy & Congestion (Mean)	β_{13}	0.2017	4.0549**	
	Random effect (SD)		-0.0374	-0.1516	
	Parking & Congestion (Mean)	β_{23}	0.1094	1.6730	
	Random effect (SD)		0.3483	4.4408**	
	Subsidy & Parking & Congestion (Mean)	β_{123}	-0.0777	-2.0364*	
	Random effect (SD)		-0.0015	-0.0088	
Model B1	ASC	β_0	0.6463	9.0793**	L(0) = - 12405.3 L(β) = - 8234.6 ρ^2 = 0.336 Number of observations: 678
	PT commuting cost subsidy (Mean)	β_1	-0.4819	-10.6053**	
	Random effect (SD)		0.5547	7.5530**	
	Additional parking fee (Mean)	β_2	-0.3476	-10.1797**	
	Random effect (SD)		0.1525	1.8057	
	Congestion charge (Mean)	β_3	-0.3687	-11.5188**	
	Random effect (SD)		-0.1549	-2.6862**	
	Subsidy & Parking (Mean)	β_{12}	-0.0077	-0.5760	
	Random effect (SD)		-0.0116	-0.2573	
	Subsidy & Congestion (Mean)	β_{13}	-0.0090	-0.7573	
	Random effect (SD)		-0.0061	-0.1621	
	Parking & Congestion (Mean)	β_{23}	0.0122	1.1383	
	Random effect (SD)		0.0395	2.4928*	
	Subsidy & Parking & Congestion (Mean)	β_{123}	-0.0016	-0.3301	
	Random effect (SD)		0.0095	1.3610	

Model C1	**ASC**	$\boldsymbol{\beta_0}$	**1.0842**	**12.3763****	L(0) = - 10704.3 L(β) = - 7548.7 ρ^2 = 0.295 Number of observations: 582
	PT commuting cost subsidy (Mean)	$\boldsymbol{\beta_1}$	**-0.5503**	**-10.3460****	
	Random effect (SD)		**0.7075**	**7.1162****	
	Additional parking fee (Mean)	$\boldsymbol{\beta_2}$	**-0.4124**	**-10.5831****	
	Random effect (SD)		**0.2320**	**2.7347****	
	Congestion charge (Mean)	$\boldsymbol{\beta_3}$	**-0.6091**	**-11.7424****	
	Random effect (SD)		**0.4574**	**5.9420****	
	Subsidy & Parking (Mean)	β_{12}	-0.0143	-0.8401	
	Random effect (SD)		0.0190	0.3822	
	Subsidy & Congestion (Mean)	β_{13}	-0.0281	-1.3297	
	Random effect (SD)		0.0043	0.0887	
	Parking & Congestion (Mean)	β_{23}	0.0023	0.1257	
	Random effect (SD)		**0.0763**	**2.6715****	
	Subsidy & Parking & Congestion (Mean)	β_{123}	0.0001	0.0115	
	Random effect (SD)		-0.0091	-0.6517	
Model A2	**ASC**	$\boldsymbol{\beta_0}$	**0.7485**	**11.7969****	L(0) = - 14035.5 L(β) = - 10023 ρ^2 = 0.286 Number of observations: 767
	PT commuting cost subsidy (Mean)	$\boldsymbol{\beta_1}$	**-0.7402**	**-12.5264****	
	Random effect (SD)		-0.2537	-1.2277	
	Additional parking fee (Mean)	$\boldsymbol{\beta_2}$	**-0.7873**	**-12.8577****	
	Random effect (SD)		0.1424	0.4272	
	Congestion charge (Mean)	$\boldsymbol{\beta_3}$	**-0.9886**	**-13.9238****	
	Random effect (SD)		0.1903	0.7575	
	Subsidy & Parking (Mean)	$\boldsymbol{\beta_{12}}$	**0.1146**	**3.4209****	
	Random effect (SD)		0.0149	0.0401	
	Subsidy & Congestion (Mean)	$\boldsymbol{\beta_{13}}$	**0.1320**	**3.2693****	
	Random effect (SD)		-0.0459	-0.1862	
	Parking & Congestion (Mean)	β_{23}	0.0621	1.0227	
	Random effect (SD)		**0.3224**	**3.9080****	
Model B2	**ASC**	$\boldsymbol{\beta_0}$	**0.6360**	**9.1868****	L(0) = - 12405.3 L(β) = - 8235.2 ρ^2 = 0.336 Number of observations: 678
	PT commuting cost subsidy (Mean)	$\boldsymbol{\beta_1}$	**-0.4770**	**-11.0862****	
	Random effect (SD)		**0.5405**	**7.8228****	
	Additional parking fee (Mean)	$\boldsymbol{\beta_2}$	**-0.3357**	**-10.2629****	
	Random effect (SD)		0.1107	1.0714	
	Congestion charge (Mean)	$\boldsymbol{\beta_3}$	**-0.3644**	**-11.6661****	
	Random effect (SD)		**-0.1486**	**-2.5391***	
	Subsidy & Parking (Mean)	β_{12}	-0.0063	-0.6547	
	Random effect (SD)		0.0088	0.1650	
	Subsidy & Congestion (Mean)	β_{13}	-0.0078	-0.9590	
	Random effect (SD)		-0.0010	-0.0297	
	Parking & Congestion (Mean)	β_{23}	0.0085	0.8101	
	Random effect (SD)		**-0.0468**	**-3.0995****	
Model C2	**ASC**	$\boldsymbol{\beta_0}$	**1.0673**	**12.6916****	L(0) = - 10704.3 L(β) = - 7550 ρ^2 = 0.295 Number of observations: 767
	PT commuting cost subsidy (Mean)	$\boldsymbol{\beta_1}$	**-0.5418**	**-11.4311****	
	Random effect (SD)		**0.5946**	**9.4385****	
	Additional parking fee (Mean)	$\boldsymbol{\beta_2}$	**-0.3938**	**-10.9392****	
	Random effect (SD)		0.1744	1.9134	
	Congestion charge (Mean)	$\boldsymbol{\beta_3}$	**-0.5830**	**-12.2387****	
	Random effect (SD)		**0.3805**	**5.4997****	
	Parking & Congestion (Mean)	β_{23}	-0.0088	-0.4953	
	Random effect (SD)		**0.0974**	**3.9669****	

* Since this mixed logit model is developed as an integrated utility function form, the sign of the coefficient of PT commuting cost subsidy is estimated as minus. However, if it transfers to separate utility function forms, it requires just the change of sign (see **Equation 3-4**).
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

In this research, the MLM with the uniform distribution is also calibrated. The results are almost the same as those of normal distribution. Therefore, "what is the best distribution in this research?" is not clear. In addition, the MLM with the lognormal distribution cannot be estimated since the values of log (0) are converged to 'infinity' and so null log-likelihood values cannot be obtained. Estimation results of the MLMs with uniform distribution are attached to **Appendix 4**. In addition, the calculation of the choice probability of the travel mode in the MLMs is attached to **Appendix 5**.

5.7. Summary

Utility functions with only alternative-specific variables are developed using binary standard logit models to investigate the most effective MSP. Many coefficients of the two-factor interaction effect, as well as all main effect coefficient of the MSP, are statistically significant while the three-factor interaction effect coefficient (β_{123}) is statistically insignificant. In addition, the ρ^2 values of models with interaction terms are higher than those of models without interaction terms, even though differences in fit are small.

In comparison of modal shift effects of the MSP, the greatest level of modal shift would be achieved by the introduction of the congestion charges, while the lowest level of modal shift would be generated by the PT commuting cost subsidies. In addition, the most powerful combination was a union between the additional parking fees and congestion charges. Meanwhile, the modal shift effects of the MSP under the same monetary level of policy intervention are also predicted. Although the order of the modal shift effect is similar to the above results, there are some exceptions.

In addition, to overcome limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors, the MLMs with normal and uniform distribution are developed. The MLMs, reflecting preference heterogeneity across individuals, are compared with the standard logit model. In terms of the ρ^2, the MLM is better than the standard logit model. However, most of the standard deviations related to the interaction effect variables are statistically insignificant. Therefore, the MLMs are not taken forward to study interactions.

Chapter 6. Review of Interaction Effects

6.1. Introduction

The chapter reviews the interaction effects of MSPs. Due to the full factorial design of the SP survey, the two-way interactions of MSPs can be analysed in the thesis. This chapter consists of five sections. Section 6.2 illustrates an overview of the interaction effects of MSPs. Section 6.3 compares the shape of the modal shift probability curve according to the change of allocation ratio of policy intervention. Section 6.4 deals with modal shift synergy effect and redundancy effect. Section 6.5 compares the difference of the modal shift probability curve between the models without and with interaction terms in accordance with the increase of policy intervention.

6.2. Overview of Interaction Effects of Modal Shift Policies

6.2.1. Main research subject

Due to a full factorial design of SP survey, detailed research of policy packaging can be possible in this research. As a result, interaction effects of the combined MSPs can be assessed more accurately. Although the combination of economic instruments and non-economic instruments can be possible, comparison of transport policies at the same or similar level or condition is very difficult. Therefore, this research focuses on three combinations of economic instruments to clearly and precisely evaluate the modal shift effects of the combined MSPs and investigate what an optimal combination is.

1) The combination of PT commuting cost subsidies and additional parking fees

The implementation of PT commuting cost subsidies alone may be a feeble solution to solve congestion problems. The introduction of additional parking fees may also be the powerless solution. However, the combination of these two MSPs may complement each weakness of the two MSPs. That is, additional parking fees may be used to finance PT commuting cost subsidies while PT commuting cost subsidies may offset adverse equity effect of additional parking fees.

2) The combination of PT commuting cost subsidies and congestion charges

The implementation of PT commuting cost subsidies alone can cause a lack of financial resource in the governmental sector. In addition, PT commuting cost subsidies can create distortion in the economy since it requires a higher level of taxation to finance PT commuting cost subsidies.

Meanwhile, the implementation of congestion charges may trigger the objection of the public. However, the combination of these two MSPs can achieve a higher level of modal shift effects, obtain political acceptance from the public, and solve financial problems.

3) The combination of additional parking fees and congestion charges

In general, although additional parking fees can obtain public acceptance relatively easily, these measures have limitations in ironing out the wide range of congestion problems. Meanwhile, although zone-based congestion charges can gain significant reduction of congestion, it can create the objection of the public. Additional parking fees can partially internalise the externalities on the road while congestion charges can partially address congestion in parking areas. Therefore, as long as there are externalities of different kinds and in different places, the combination of these two MSPs can be facilitated effectively (SPECTRUM, 2004, p26).

6.2.2. Issues of interaction effect research

The research on interaction effects of the MSP focuses on two issues. First, one of the main issues is whether the interaction effect can contribute to the enhancement of validity of the model or not. In general, the goodness of fit of the model can be verified by the ρ^2. The ρ^2 is usually used to evaluate how well the model fits or explains the observed data. The closer to 1 the value, the better the goodness of fit of a model. In terms of the ρ^2 values, models 1, models with interaction terms including statistically insignificant coefficients, and models 2, models with interaction terms comprised of only statistically significant coefficients, are higher than models 0, models without interaction terms (see **Table 6-1**). As a result, it is approved that models with interaction variables are better than models without interaction variables.

Table 6-1. Comparison of rho-squared index of the standard logit models with alternative specific variables

Classification	Model A0	Model B0	Model C0	Model A1	Model B1	Model C1	Model A2	Model B2	Model C2
ρ^2	0.282	0.324	0.278	**0.286**	**0.327**	**0.281**	**0.286**	**0.327**	**0.280**

Second, in a comparison of modal shift effects of both an individual MSP and the combined MSPs, whether interaction effect of the MSPs is positive or negative can be understood. As indicated in **Table 5-1**, all the coefficients associating with two-way interactions (β_{12}, β_{13}, and β_{23}) have positive signs. Since all the coefficients related to three-way interactions of MSP, sometimes called second-order interactions (β_{123}), are statistically insignificant in all the models 2, the research of three-way interactions is excluded in this research. In addition, since models 2 are models with interaction terms comprised of only statistically significant coefficients, models 2 are selected as the main models.

As shown in **Table 6-2**, all the two-way interactions in models 2 have positive signs in the utility function of car use. The positive signs in the utility function of car use contribute to the increase of the utility of car use. Therefore, judging simply from the signs of coefficients related to two-way interaction, the implementation of package MSPs seems to create negative modal shift effects.

In many cases of research, it is widely recognized that simultaneous implementation of two MSPs can overcome the weakness of a single MSP and create a positive synergy effect. Therefore, this research concentrates on both whether modal shift synergy effects exist or not and what the magnitude of modal shift synergy effects is by using the quantified method. The main issue may be as to whether the modal shift effect of the two combined MSPs, which is composed of one half MSP and the other half of MSP, is greater than the single MSP alone or not.

In this research, the utility functions of travel mode choice models with interaction terms are as follows. The following utility functions can calculate the probability of travel mode.

$$\mathrm{V}_{car} = \beta_0 + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j \quad (6\text{-}1)$$

$$\mathrm{V}_{PT} = \beta_1 \cdot Subsidy_j \quad (6\text{-}2)$$

$$\mathrm{V}_{car} - \mathrm{V}_{PT} = \beta_0 - \beta_1 \cdot Subsidy_j + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j \quad (6\text{-}3)$$

Table 6-2. The coefficients of model A2, model B2, and model C2

Classification	Beta	Model A2 coefficient	Model B2 coefficient	Model C2 coefficient
Alternative-Specific Constant	β_0	0.7331	0.3341	0.4212
PT commuting cost subsidy	β_1	0.7173	0.2015	0.1285
Additional parking fee	β_2	-0.7926	-0.3121	-0.2928
Congestion charge	β_3	-0.9845	-0.3253	-0.3757
Subsidy & Parking	β_{12}	**0.1270**	**0.0186**	**-**
Subsidy & Congestion	β_{13}	**0.1494**	**0.0189**	**-**
Parking & Congestion	β_{23}	**0.1848**	**0.0213**	**0.0303**
Subsidy & Parking & Congestion	β_{123}	-	-	-

* The estimation result is based on the separate utility functions such as the utility function of car use (Equation 6-1) and the utility function of PT use (Equation 6-2).

6.3. Shape of the Modal Shift Probability Curve According to the Change of Allocation Ratio of Policy Intervention

In reality, every transport policy has limitations of implementation such as political acceptability, budget limitation, legal barrier, and congested transport situation. That is, unlimited policy intervention is impossible in the real world. Therefore, in the study, under the assumption of limitation of policy intervention (e.g. 5,000 won, £ 2.78) the modal shift probability curve in models 2 (i.e. model A2, model B2, and model C2) are compared in order to understand the two-way interaction effects between the two MSPs. Since models 2 are models with interaction terms comprising only statistically significant coefficients, the comparative research can offer significant information on two-way interaction effect. As shown in **Table 6-2**, model C2 does not have statistically significant coefficients β_{12} and β_{13} whereas model A2 and model B2 have all the two-way interaction coefficients that are statistically significant. Therefore, model A2 and model B2 are focused in the research.

6.3.1. Comparison of interaction effect between public transport commuting cost subsidies and additional parking fees

6.3.1.1. Comparison of graphs, having interaction variables, and graphs, not having interaction variables

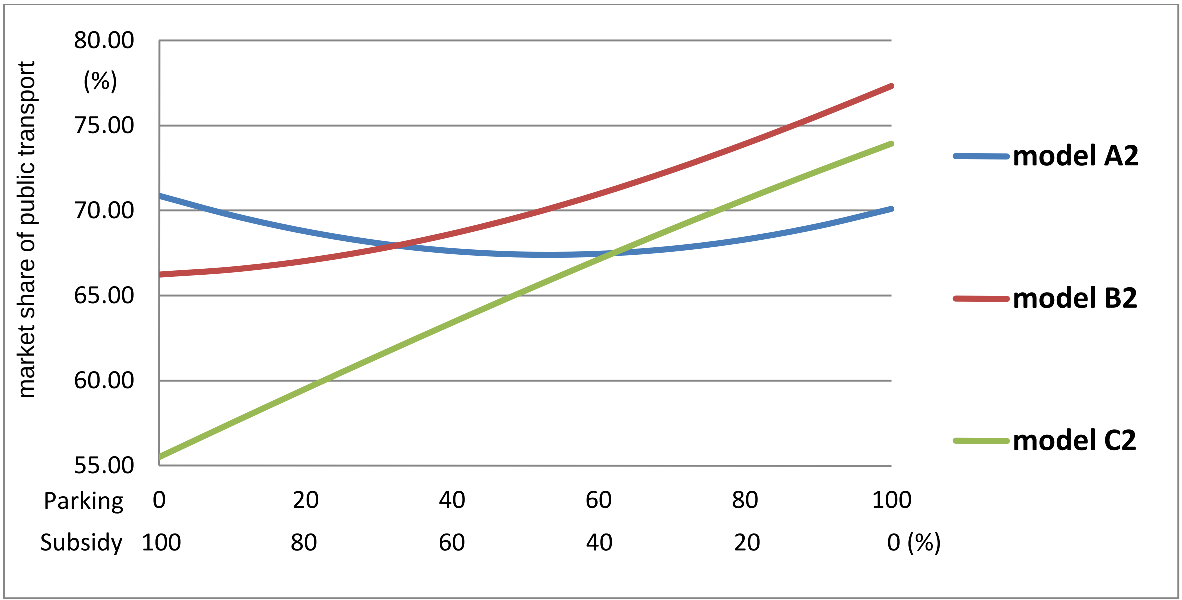
As shown in **Table 6-3**, while the independent implementation of the additional parking fee (100%) shows the highest level of the choice probability of PT in model B2 and model C2, the exclusive implementation of PT commuting cost subsidies (100%) represents the highest level of the choice probability of PT in model A2 under the limited policy intervention. Although the highest level of the choice probability of PT depends on the type of models, the result indicates that the highest level of the modal shift effect can be obtained by just the implementation of a more powerful MSP alone, not the implementation of the combined MSPs.

Table 6-3. The market share of PT according to the change of allocation ratio of policy intervention between PT commuting cost subsidies and additional parking fees under the limited policy intervention (5,000 won)

Parking (%)	0	10	20	30	40	50	60	70	80	90	100
Subsidy (%)	100	90	80	70	60	50	40	30	20	10	0
Model A2 (%)	**70.87**	69.71	68.78	68.08	67.62	67.41	67.46	67.76	68.30	69.08	70.10
Model B2 (%)	66.23	66.53	67.03	67.74	68.63	69.71	70.96	72.37	73.91	75.57	**77.32**
Model C2 (%)	55.51	57.53	59.52	61.49	63.41	65.30	67.13	68.92	70.65	72.33	**73.94**

In **Figure 6-1**, the vertical axis shows the estimated market share of PT (modal shift probability). On the other hand, the horizontal axis illustrates the change of distribution ratio of policy intervention between PT commuting cost subsidies and additional parking fees in the range from 0% to 100% or from 100% to 0% under the limited budget or levy of 5,000 won (£2.78).

Figure 6-1. The modal shift probability curve according to the change of allocation ratio of policy intervention between PT commuting cost subsidies and additional parking fees under the limited policy intervention (5,000 won)



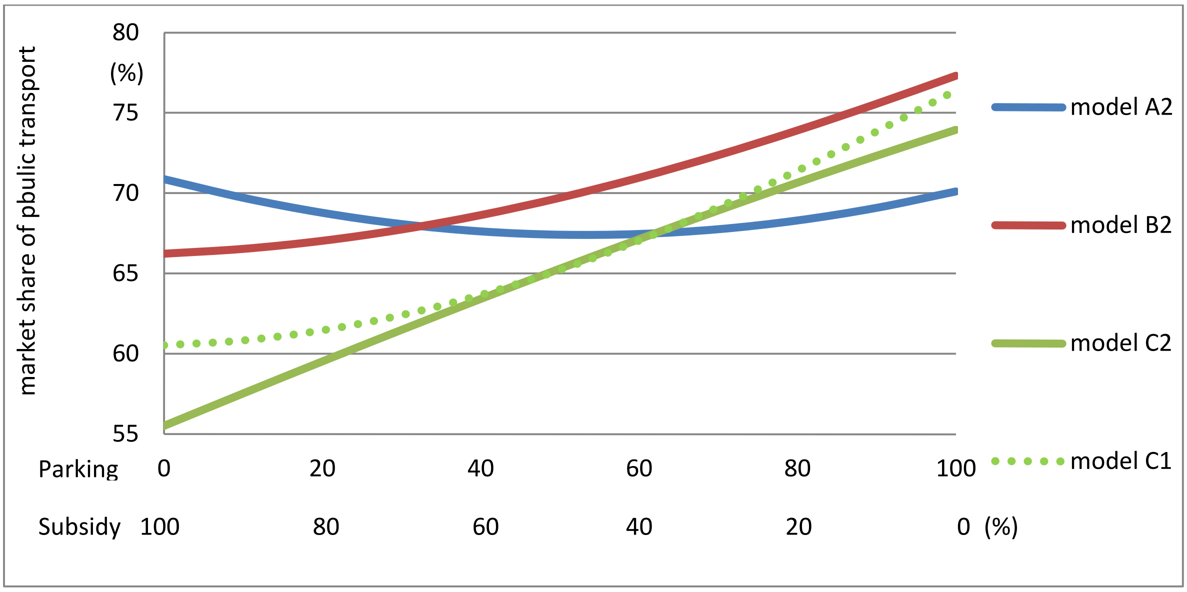
Model C2 (see green graph), which possesses no statistically significant interaction coefficient (β_{12}), represents the shape of a straight line. That is, it can be inferred that if there are no interaction between the MSPs, the modal shift probability curve will show a straight line, not a skewed curve. In addition, as the distributional ratio of the additional parking fees rises, the market share of PT goes up consistently. When only the additional parking fee (100%) is implemented, the market share of PT is the highest. It can be concluded that when there are no interactions between the MSPs, the modal shift probabilities of additional parking fees are always greater than those of PT commuting cost subsidies.

Although model A2 (blue graph), having statistically significant interaction coefficient (β_{12}), has an approximately even shaped and curved line, both extreme points are higher than other combined points. It indicates that the modal shift effects of an individual MSP are greater than those of the combined MSPs. In addition, model A2, which is based on the level (e.g. 0, 1, and 2) of MSP, predicts that modal shift probabilities of PT commuting cost subsidies are higher than those of other models. Although the value of the coefficient (β_2) is larger than coefficient (β_1), it seems that the influence of level of the attribute is more powerful than the influence of the coefficient in the utility function.

Model B2 (red graph) also has statistically significant interactions. In terms of the shape of a line as a curved line, model B2 is similar to model A2 (blue graph). However, the implementation of solo additional parking fees (100%) is predicted as the highest market share of PT. All in all, if interaction effects exist, the modal shift probability curve shows a curve-shaped line. Thus, the interaction effects of the MSP seem to mitigate extreme choice preference. In addition, since the magnitude of the coefficient β_{12} is relatively small (0.0186) (See **Table 6-2**), the change of slope of the curved line seems to be relatively small.

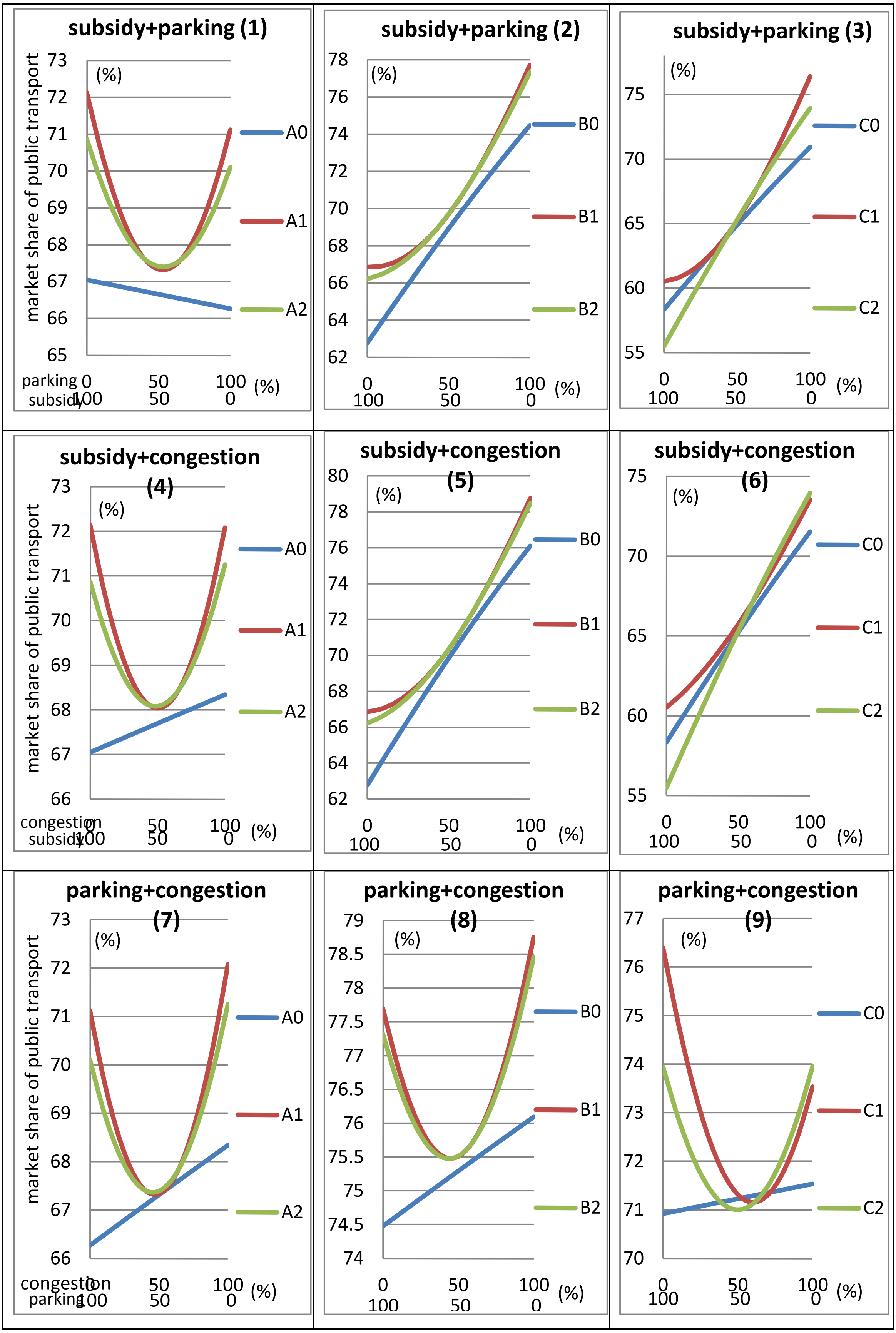
6.3.1.2. Comparison of models with interactive coefficients and models without interactive coefficients

Figure 6-2. Comparison of model C1 and model C2



In a comparison of the dotted green graph (model C1) with the straight green graph (model C2) in **Figure 6-2**, model C1, a model with an interaction coefficient (β_{12}), seems to predict higher market share of PT than model C2, a model without an interaction coefficient. As shown in **Figure 6-3**, every graph shows the similar results. That is, a model without an interaction coefficient (straight line) seems to be located in the below part whereas a model with an interaction coefficient (curved line) seems to be situated in the upper part. As shown in **Figure 6-3**, although the market share of PT for each model depends on the magnitude of the various coefficients in the utility function, it is obvious that models with an interaction coefficient show a commonly higher market share of PT than a model without an interaction coefficient on the whole. This result corresponds to existing study (Ortúzar et al., 1997). In addition, an interesting indication is that as interaction is stronger, the shape of the line seems to become a bowl-shaped line. On the contrary, as the interaction effect is weak, the shape of the line seems to be formed as a more approximate straight line.

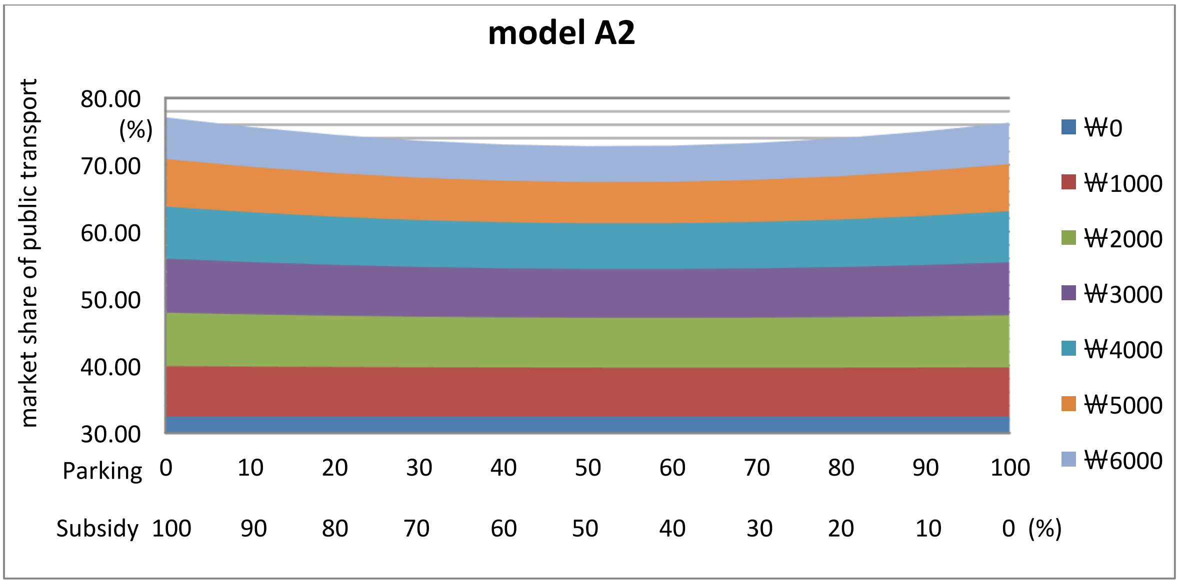
Figure 6-3. Comparison of modal shift probability curve of the combined MSPs

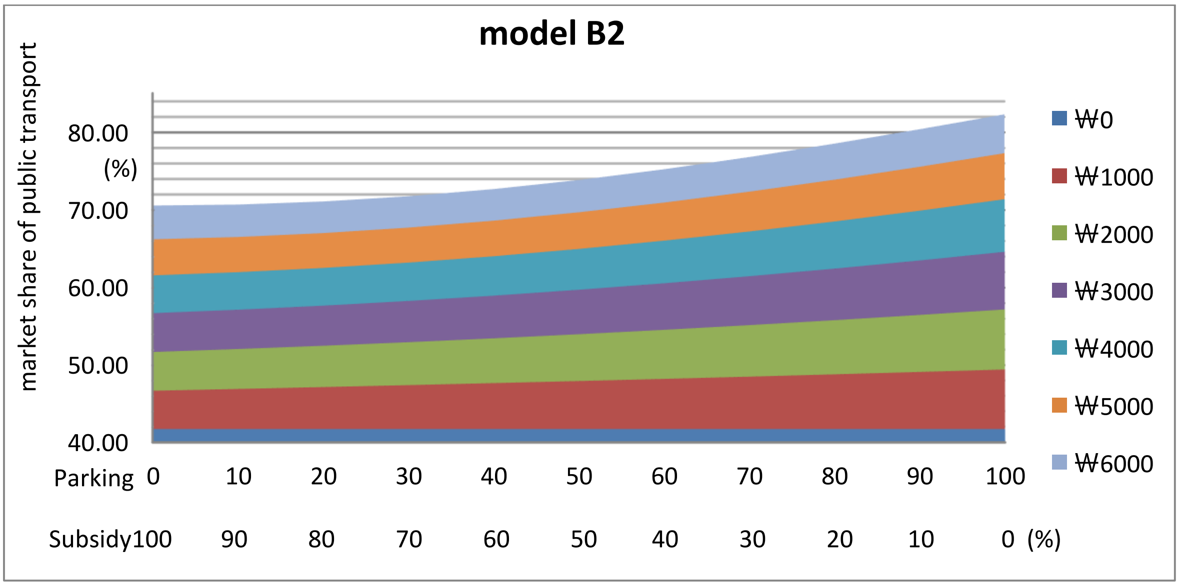


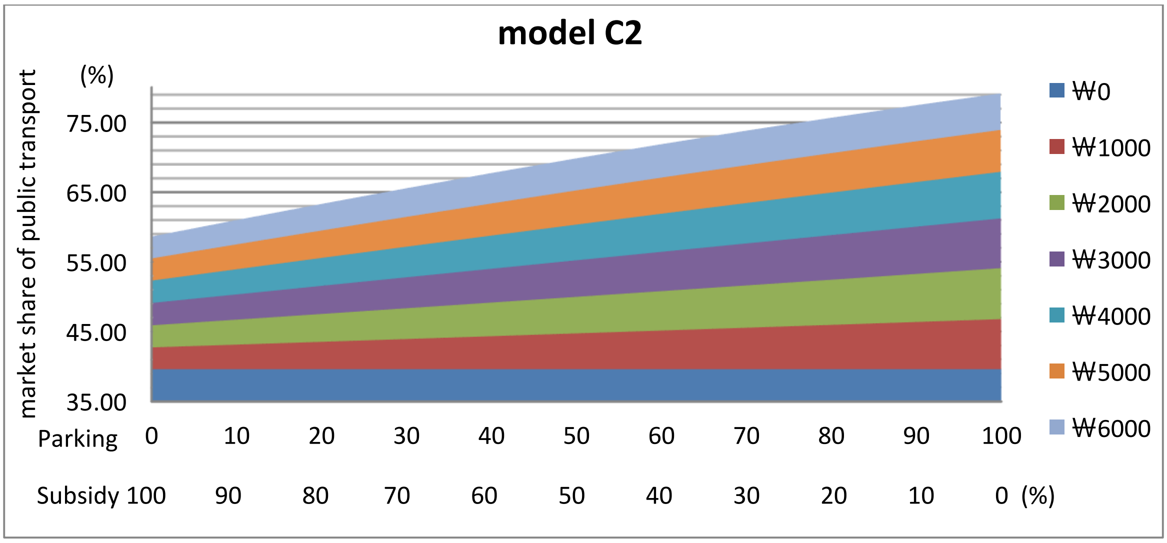
6.3.1.3. Interaction effects of the combined MSPs in accordance with the implementation of diverse policy interventions

As shown in **Figure 6-4**, as the magnitude of the policy intervention goes up from 0 won to 6,000 won, the interaction effects between them are shown clearly. Model C2 indicates apparently that all the graphs represent the straight lines. That is, without the interaction effects, the modal shift effects of the MSP would always be the same. The higher the allocation ratio of a powerful MSP, the greater modal shift effects of a more powerful MSPs is. The higher allocation ratio of additional parking fees can obtain higher modal shift effects.

Figure 6-4. The modal shift probability curves in accordance with the change of allocation ratio of policy intervention between PT commuting cost subsidies and additional parking fees







Meanwhile, it can be inferred that if strong interaction effects exist, the market share of PT at the middle part of the graphs will be the lowest. If there are strong interaction effects between them, the modal shift probability curves are shaped as concave curved graphs (model A2 in **Figure 6-4**). On the contrary, if there are no interaction effects, the modal shift probability curves are shaped as upward straight lines (model C2). All in all, the shape of the modal shift probability curve depends on whether interaction coefficient exists or not.

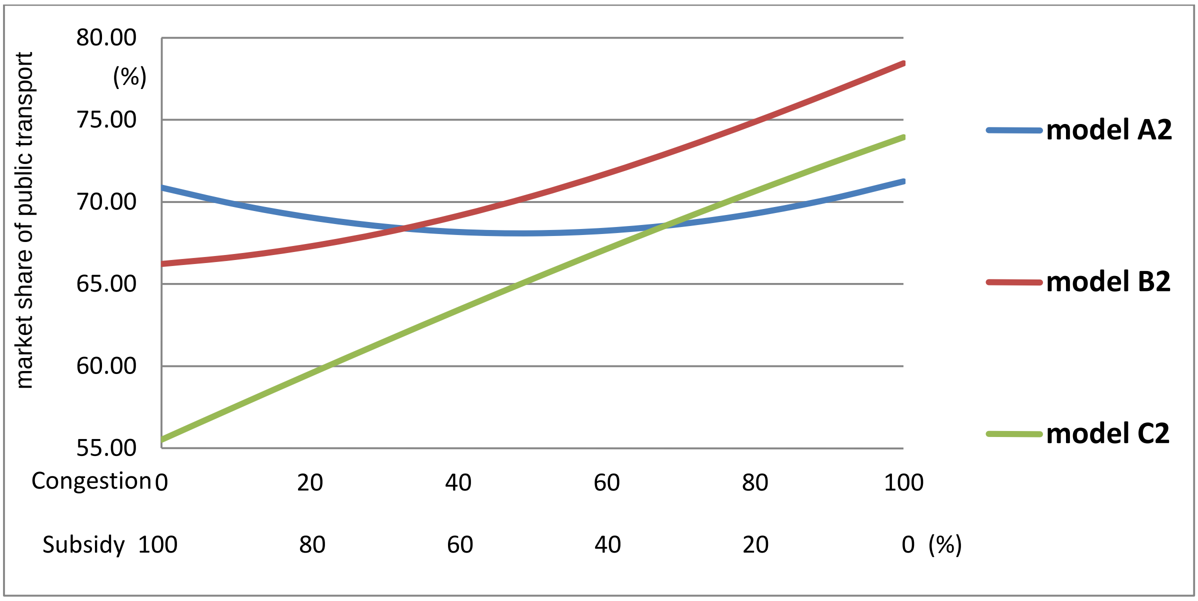
6.3.2. Comparison of interaction effect between public transport commuting cost subsidies and congestion charges

Table 6-4 and **Figure 6-5** show the market share of PT according to the change of allocation ratio of policy intervention between PT commuting cost subsidies and congestion charges under the limited policy intervention (5,000 won). **Figure 6-5** is similar to **Figure 6-1** in the aspect of shape and trends even though inclinations of graphs are different. As shown in **Table 6-4**, the highest level of modal shift effect would be obtained by just the implementation of exclusive congestion charges (100%), not the implementation of the combined MSPs.

Table 6-4. The market share of PT according to the change of allocation ratio of policy intervention between PT commuting cost subsidies and congestion charges under the limited policy intervention (5,000 won)

Congestion (%)	0	10	20	30	40	50	60	70	80	90	100
Subsidy (%)	100	90	80	70	60	50	40	30	20	10	0
Model A2 (%)	70.87	69.85	69.05	68.49	68.16	68.08	68.25	68.65	69.29	70.17	**71.25**
Model B2 (%)	66.23	66.66	67.30	68.13	69.16	70.37	71.74	73.25	74.89	76.64	**78.46**
Model C2 (%)	55.51	57.53	59.52	61.49	63.42	65.30	67.14	68.93	70.66	72.33	**73.95**

Figure 6-5. The modal shift probability curve according to the change of allocation ratio of policy intervention between PT commuting cost subsidies and congestion charges under the limited policy intervention (5,000 won)



6.3.3. Comparison of interaction effect between the additional parking fees and congestion charges

As shown in **Table 6-5** and **Figure 6-6**, the independent implementation of congestion charges (100%) shows the highest level of the market share of PT in model A2, model B2 and model C2. That is, the result indicates that the highest level of modal shift probability can be obtained by the implementation of exclusive congestion charges. In addition, the implementation of the two MSP at an almost equal allocation ratio of policy intervention at the same time causes the lowest level of the market share of PT. It indicates that the equally distributed implementation of the two MSPs can make the worst result of modal shift effects.

Table 6-5. The market share of PT according to the change of allocation ratio of policy intervention between additional parking fees and congestion charges under the limited policy intervention (5,000 won)

Congestion (%)	0	10	20	30	40	50	60	70	80	90	100
Parking (%)	100	90	80	70	60	50	40	30	20	10	0
Model A2 (%)	70.10	69.04	68.24	67.69	67.40	67.39	67.65	68.17	68.96	69.99	**71.25**
Model B2 (%)	77.32	76.59	76.03	75.66	75.49	75.52	75.73	76.15	76.75	77.52	**78.46**
Model C2 (%)	73.94	72.90	72.08	71.48	71.12	71.00	71.12	71.49	72.08	72.91	**73.95**

As shown in **Figure 6-6**, all the graphs show curved lines since all the graphs have statistically significant interactions between the two MSPs. Model B2, which reflects individual's PT commuting cost, predicts the highest modal shift probability of congestion charges. In the case of model C2 (green graph), which reflected by reduced time values with regard to congestion charges as well as in an individuals' PT commuting cost, the reduced time effect of congestion charges seems to influence the weakness of modal shift effects. Model A2, which is based on the level unit, expresses the lowest modal shift probability of the MSP (blue graph). Overall, the shapes of graphs show the interaction effect clearly even though the differences of the height of the graph exists. It indicates that interaction effects affect the market share of PT significantly.

Figure 6-6. The modal shift probability curve according to the change of allocation ratio of policy intervention between additional parking fees and congestion charges under the limited policy intervention (5,000 won)

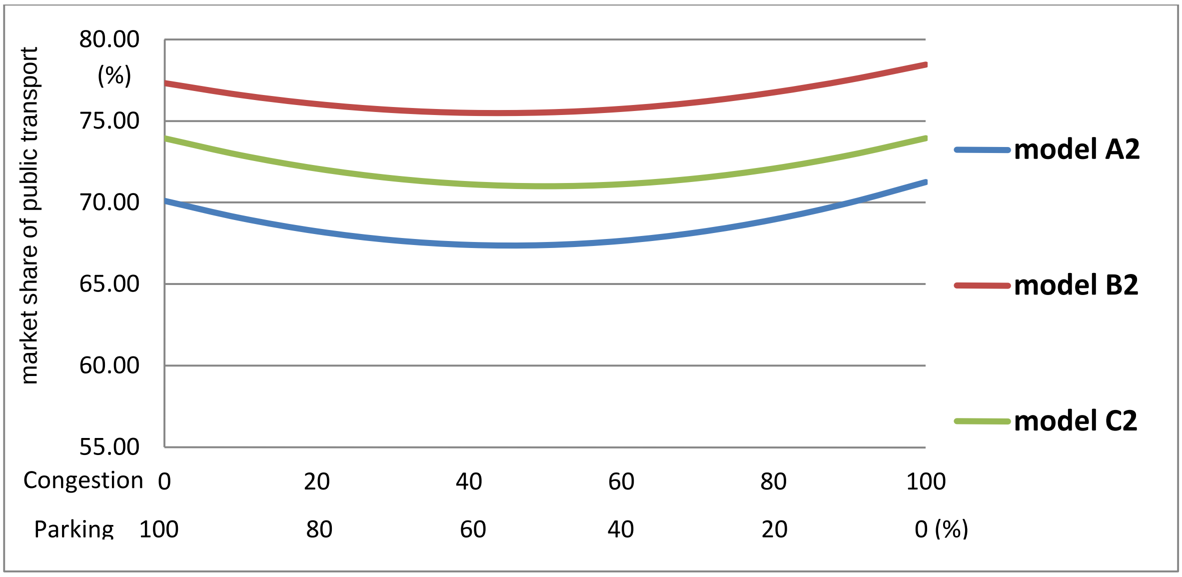
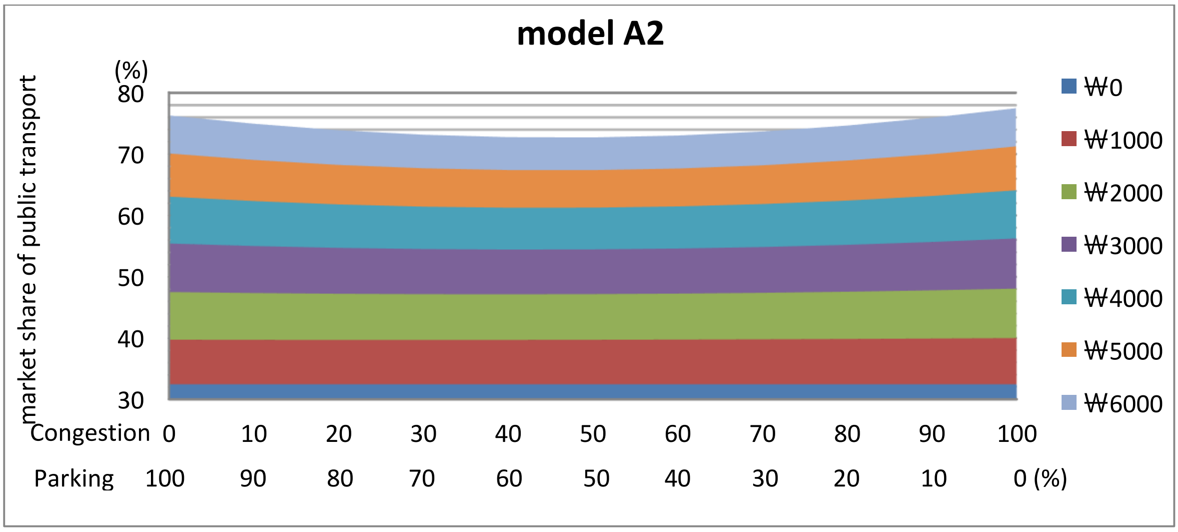
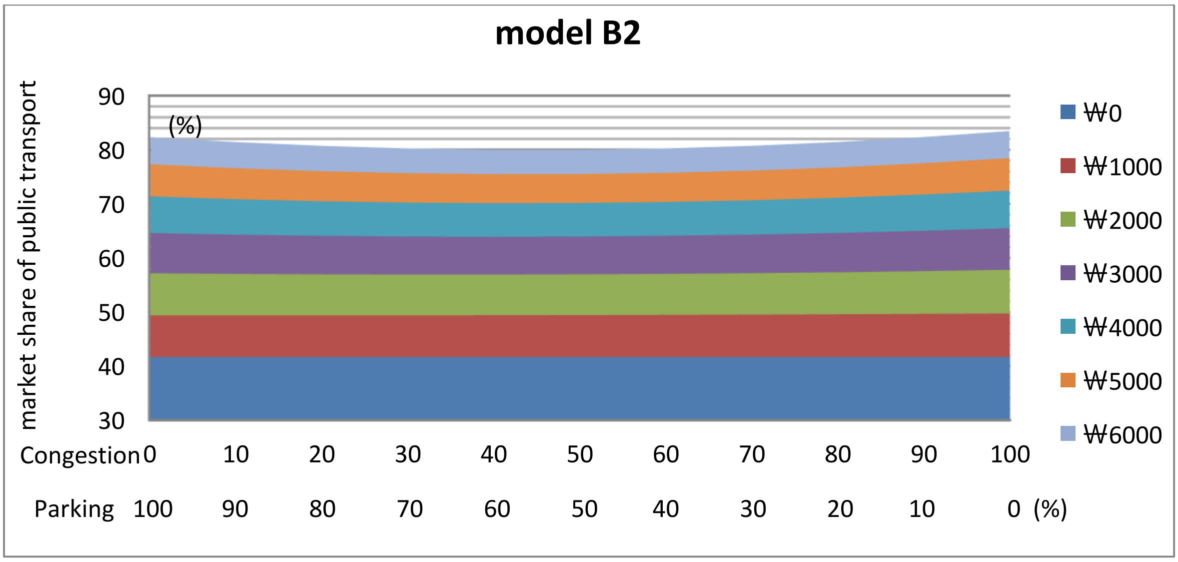
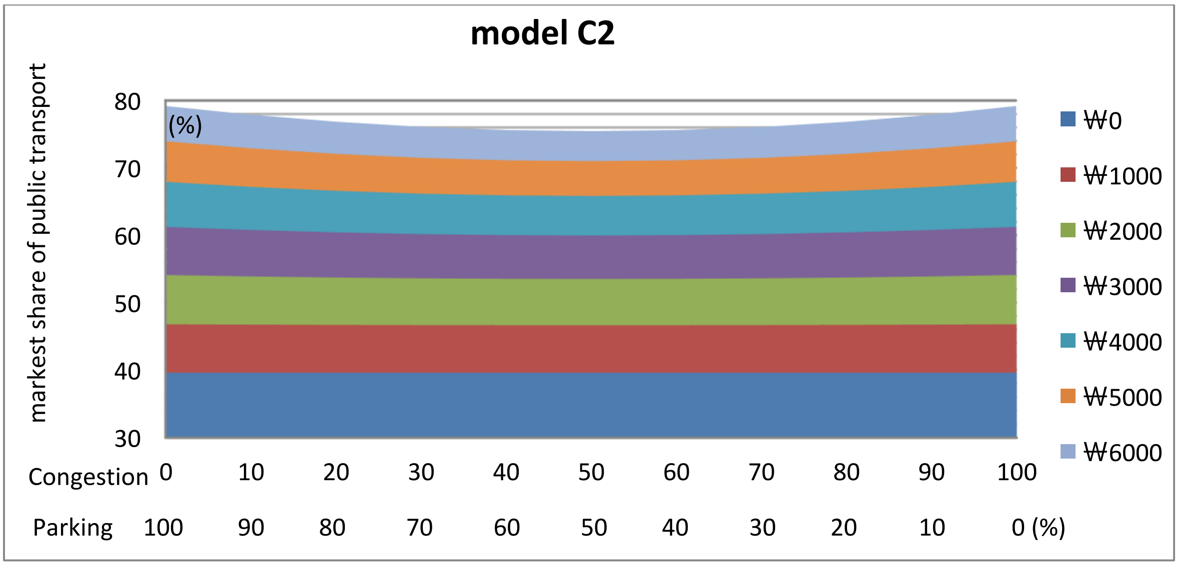


Figure 6-7 shows the modal shift probability curve in accordance with the change of allocation ratio of policy intervention between the additional parking fees and congestion charges.

Figure 6-7. The modal shift probability curve in accordance with the change of allocation ratio of policy intervention between the additional parking fees and congestion charges




model B2
market share of public transport
90
80
70
60
50
40
30
(%)
Congestion 0 10 20 30 40 50 60 70 80 90 100
Parking 100 90 80 70 60 50 40 30 20 10 0 (%)
₩0
₩1000
₩2000
₩3000
₩4000
₩5000
₩6000


model C2
market share of public transport
80
70
60
50
40
30
(%)
Congestion 0 10 20 30 40 50 60 70 80 90 100
Parking 100 90 80 70 60 50 40 30 20 10 0 (%)
₩0
₩1000
₩2000
₩3000
₩4000
₩5000
₩6000

6.4. Modal Shift Synergy Effect

6.4.1. Concept of the modal shift synergy effect

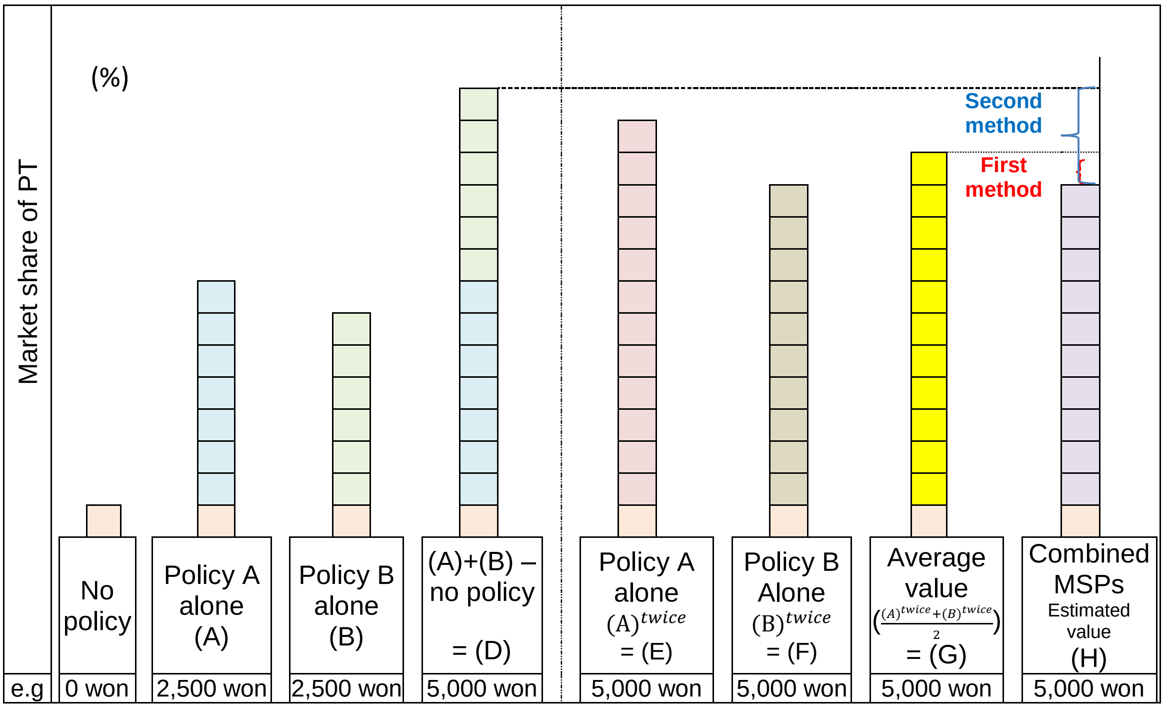
To identify the meaning of the interaction effects, the concept of synergy can be introduced. Synergy is defined as “an effect occurring when the simultaneous use of two policies offers greater benefits than the sum of the benefits of using either one of them alone” (May et al., 2004; Habibian and Kermanshah, 2011). Therefore, the modal shift synergy effect can be defined as modal shift effect being greater than the sum of their individual modal shift effect of using either one of them alone when two or more MSPs are implemented at the same time. The benefits of two combined MSPs, such as MSP A and MSP B, are greater than the sum of the individual MSP. This can be expressed as the Benefit (A + B) > Benefit (A) + Benefit (B). Additionality can be written as the Benefit (A + B) = Benefit (A) + Benefit (B) whereas complementarity might be represented as the Benefit (A + B) > Benefit (A), Benefit (A+B) > Benefit (B). This means that the benefits of one measure are strengthened by the benefits of another (Preston, 2010, 2012a). To identify whether synergy can be found or not, the concept of the modal shift synergy effect could be defined as follows.

$$\text{Modal shift synergy effect: MSSE } (A_a+B_b) = \text{MSE } (A_a+B_b) - [\text{MSE } (A_a) + \text{MSE } (B_b)] \qquad (6\text{-}4)$$

where MSE (A_a) and MSE (B_b) are separate modal shift effect achieved by the implementation of level a of MSP A and level b of MSP B, MSE (A_a+B_b) is modal shift effect generated by simultaneously implementing level a of MSP A and level b of MSP B. Modal shift effects from car to PT can be treated as a proxy of the benefits obtained by implementing MSPs.

Two methods can be used to measure modal shift synergy effect of the combined MSPs. The first method is to compare the difference between ‘the estimated value [(H) in **Figure 6-8**] of modal shift probability for the combination of MSP A and MSP B’ and ‘the average value [(G)] of the sum of modal shift probability for MSP A alone [(E)] and MSP B alone [(F)]’. For instance, ‘the estimated values of the modal shift probability for the combined MSPs under the policy intervention (5,000 won)’ can be compared with ‘the average value (1/2) of the sum (10,000 won) of modal shift probability of MSP A alone under the policy intervention (5,000 won) and modal shift probability of MSP B alone under the policy intervention (5,000 won)’. Through this method, the modal shift synergy effect of the two combined MSPs can be calculated according to the change of allocation ratio of policy intervention (e.g. subsidy 0% of total policy intervention: parking 100% → subsidy 10%: parking 90%). The second method is to compare the difference between ‘the estimated value [(H) in **Figure 6-8**] of modal shift probability for the combination of MSP A and MSP B [e.g. MSE (A_a+B_a)]’ and ‘the sum [(D)] of modal shift probability of MSP A alone [(A)] an MSP B alone [(B)] (e.g. [MSE (A_a) + MSE (B_b)])’. For example, ‘the estimated values of the modal shift probability for the combined MSPs between MSP A and MSP B (e.g. 50% : 50%) with the total policy intervention (5,000 won)' can be compared with 'the sum of modal shift probability of MSP A alone under the policy intervention (2,500 won) and MSP B alone under the policy intervention (2,500 won)'. This method may be more faithfully compliant with the definition of synergy effect. **Figure 6-8** show the concept of the two methods for the modal shift synergy effect.

Figure 6-8. Concept of the two methods of the calculation for modal shift synergy effect



6.4.2. Calculation of the modal shift synergy effect

In the first instance, the first method is applied to understand the modal shift synergy effect. In **Table 6-6**, if a PT commuting cost subsidy alone is implemented, the market share of PT will mean MSE (A_a) in **Equation 6-4**. In addition, if an additional parking fee alone is implemented, the market share of PT will imply MSE (B_b) in **Equation 6-4**. For example, in the case of model A2, when implementing the combined MSPs within policy intervention of 5,000 won, MSE (A_a) will be 70.87 and MSE (B_b) will be 70.10. The average value of two values $(\frac{\text{MSE }(A_a)+\text{MSE }(B_b)}{2})$ is 70.48. Since its value implies the average value of the simple sum of the modal shift probability for each MSP alone under the condition of policy intervention of 5,000 won, there is no interaction between the single MSPs. As shown in **Table 6-6**, the differences between the average modal shift probability value (70.48) of two individual MSPs and the modal shift probability values (e.g. 70.87, 69.71, and 68.78) from allocation ratio of the two MSPs can be obtained. These difference values (e.g. 0.38, -0.77, and -171) under the allocation ratio of the two MSPs may be "deviated modal shift synergy effects". Although there are deviations derived from the use of average values, these deviations can be removed by subtracting the estimated deviations derived from a trend line of deviation values (e.g. 0.38, 0.30, and 0.23). In this case, the deviations mean difference values between the average values and pure modal shift synergy effects. The values of deviation have a symmetrical structure on both sides of the centre. In addition, the endpoints on both sides may have maximum deviations (e.g. 0.38 and -0.38). Thus, every deviation value on the trend line can be easily obtained. Therefore, after deducting the deviations derived from the use of average values, the values of the rest can be regarded as “net modal shift synergy effects of the two combined MSPs”. That is, the differences of market share of PT between individual MSP and the two combined MSPs can be interpreted as “net modal shift synergy effects of the MSP”.

Table 6-6. The net modal shift synergy effects of the combined MSPs (PT commuting cost subsidies and additional parking fees) in accordance with the change of allocation ratio of policy intervention

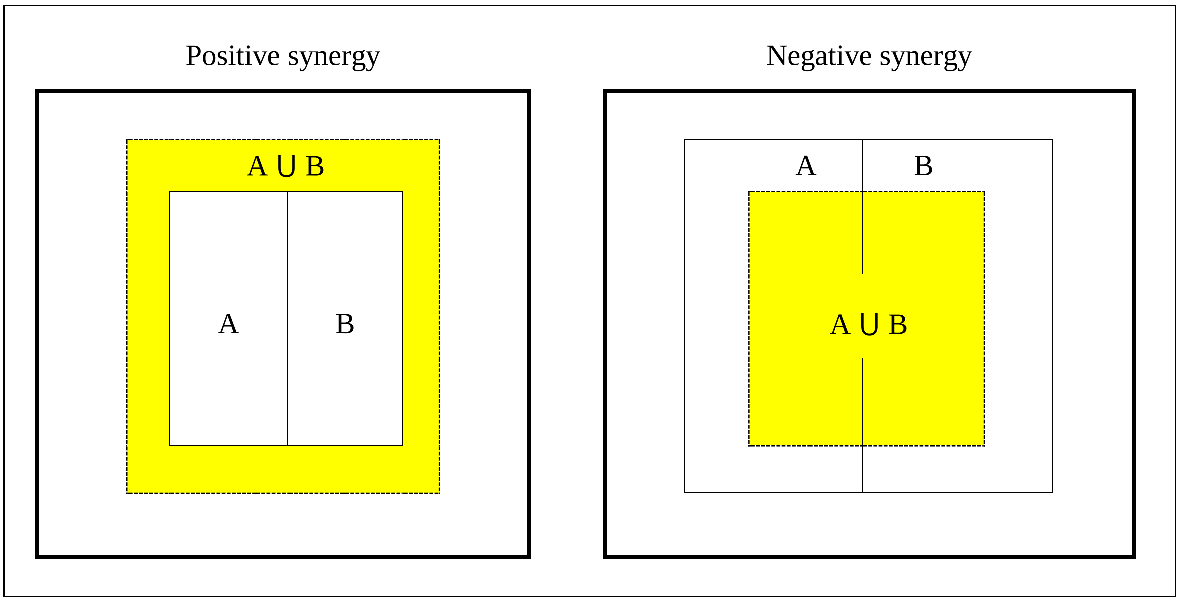
Parking (%)		0	10	20	30	40	50	60	70	80	90	100
Subsidy (%)		100	90	80	70	60	50	40	30	20	10	0
Model A2												(unit : %)
Market share of PT (X)	0 won	32.45	32.45	32.45	32.45	32.45	32.45	32.45	32.45	32.45	32.45	32.45
	1,000 won	39.92	39.86	39.80	39.75	39.72	39.70	39.68	39.68	39.69	39.71	39.75
	2,000 won	47.89	47.65	47.45	47.30	47.20	47.14	47.12	47.16	47.23	47.36	47.53
	3,000 won	55.98	55.46	55.05	54.74	54.53	54.42	54.42	54.52	54.72	55.02	55.43
	4,000 won	63.75	62.91	62.24	61.74	61.41	61.25	61.27	61.46	61.83	62.36	63.07
	5,000 won	**70.87**	**69.71**	**68.78**	**68.08**	**67.62**	**67.41**	**67.46**	**67.76**	**68.30**	**69.08**	**70.10**
	6,000 won	77.09	75.67	74.50	73.62	73.05	72.80	72.88	73.28	73.99	75.01	76.30
Deviated modal shift synergy effect (X – average value of two MSPs alone) (A)	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0.09	0.02	-0.04	-0.08	-0.11	-0.14	-0.15	-0.15	-0.14	-0.12	-0.09
	2,000 won	0.18	-0.06	-0.26	-0.41	-0.51	-0.57	-0.59	-0.55	-0.48	-0.35	-0.18
	3,000 won	0.27	-0.24	-0.65	-0.96	-1.17	-1.28	-1.28	-1.18	-0.98	-0.68	-0.27
	4,000 won	0.34	-0.49	-1.17	-1.67	-2.00	-2.16	-2.14	-1.95	-1.58	-1.05	-0.34
	5,000 won	**0.38**	**-0.77**	**-1.71**	**-2.41**	**-2.86**	**-3.07**	**-3.03**	**-2.73**	**-2.19**	**-1.40**	**-0.38**
	6,000 won	0.40	-1.03	-2.19	-3.07	-3.64	-3.89	-3.82	-3.42	-2.70	-1.69	-0.40
Deviation from use of average values (B)	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0.09	0.07	0.05	0.04	0.02	0	-0.02	-0.04	-0.05	-0.07	-0.09
	2,000 won	0.18	0.14	0.11	0.07	0.04	0	-0.04	-0.07	-0.11	-0.14	-0.18
	3,000 won	0.27	0.22	0.16	0.11	0.05	0	-0.05	-0.11	-0.16	-0.22	-0.27
	4,000 won	0.34	0.27	0.20	0.14	0.07	0	-0.07	-0.14	-0.20	-0.27	-0.34
	5,000 won	**0.38**	**0.30***	**0.23****	**0.15*****	**0.08******	**0**	**-0.08**	**-0.15**	**-0.23**	**-0.30**	**-0.38**
	6,000 won	0.40	0.32	0.24	0.24	0.08	0	-0.08	-0.16	-0.24	-0.32	-0.40
Net modal shift synergy effect (C) = A-B	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0	-0.05	-0.09	-0.12	-0.13	-0.14	-0.13	-0.11	-0.09	-0.05	0
	2,000 won	0	-0.20	-0.36	-0.48	-0.55	-0.57	-0.55	-0.48	-0.37	-0.21	0
	3,000 won	0	-0.46	-0.82	-1.07	-1.23	-1.28	-1.23	-1.08	-0.82	-0.46	0
	4,000 won	0	-0.77	-1.37	-1.80	-2.07	-2.16	-2.07	-1.81	-1.38	-0.78	0
	5,000 won	**0**	**-1.08**	**-1.94**	**-2.56**	**-2.94**	**-3.07**	**-2.95**	**-2.58**	**-1.96**	**-1.10**	**0**
	6,000 won	0	-1.34	-2.43	-3.31	-3.72	-3.89	-3.74	-3.26	-2.46	-1.37	0

* The average value of two individual MSP in model A2 → 0 won: 32.45%, 1,000 won: 39.83%, 2,000 won: 47.71%, 3,000 won: 55.7%, 4,000 won: 63.41%, 5,000 won: 70.48% (= (70.87 + 70.10)×(1/2)), 6,000 won: 76.69% (= (77.09 + 76.30)×(1/2))

* 0.30* = 0.38×(4/5), 0.23** = 0.38×(3/5), 0.15*** = 0.38×(2/5), 0.08**** = 0.38×(1/5)

Even though the definition of synergy is different from that of May et al. (2006), the modal shift synergy effect can be defined as the modal shift effect being different from the sum of their individual modal shift effect of using either one of them alone when two or more MSPs are implemented simultaneously. Therefore, in terms of the occurrence of different effects from the sum of their individual modal shift effect of using either one of them alone, the negative effect can be called as negative modal shift synergy effects. **Figure 6-9** compares the concept of positive synergy and negative synergy. It indicates that a negative synergy effect can exist as well as a positive synergy one.

Figure 6-9. Comparison of positive synergy and negative synergy



In this case, the negative modal shift synergy effects occur. (C) row in **Table 6-6** is expressed in the graphs in **Figure 6-10**. **Figure 6-10** shows the net modal shift synergy effects in model A2. That is, the modal shift synergy effect between PT commuting cost subsidies and additional parking fees illustrates negative results. These negative results can be called as negative modal shift synergy effects. In this case, since either the market share of PT with PT commuting cost subsidies alone or additional parking fees alone are always higher than those of any combinations of MSPs, even complementarity ones do not exist (May et al., 2004). That is, if there is no additional input of different policy intervention, complementarity cannot occur. In addition, the lowest value of the modal shift synergy effects between PT commuting cost subsidies and additional parking fees is found at the equal allocation ratio of policy intervention. That is, the equal policy intervention (e.g. subsidy 50% : parking 50%) produces maximum negative modal shift synergy effects.

Figure 6-10. The net modal shift synergy effects of the combined MSPs (PT commuting cost subsidies and additional parking fees) in accordance with the change of allocation ratio of policy intervention

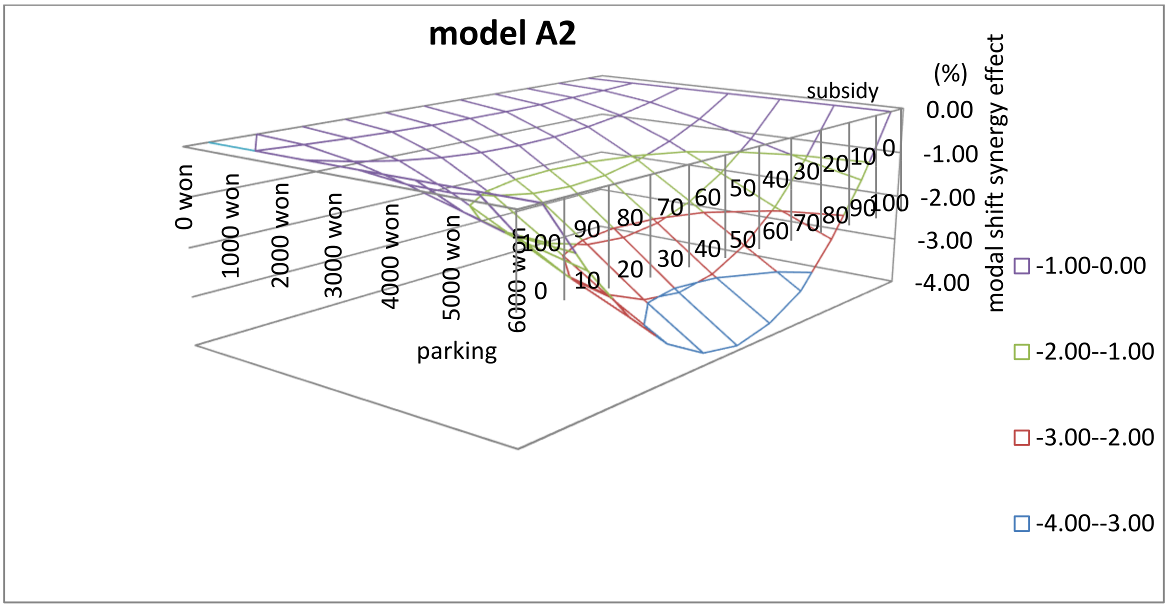


Table 6-7 shows the net modal shift synergy effects of various combined MSPs in accordance with the change of allocation ratio of the two MSPs. The calculation of the net modal shift synergy effects of the combined MSPs is the same as that of **Table 6-6**. Each net modal shift synergy effects of the combined MSPs in **Table 6-7** can be expressed as the graphs like **Figure 6-10**. All the graphs drawn from the values in **Table 6-7** are similar to those of **Figure 6-10**.

Table 6-7. Net modal shift synergy effects of various combined MSPs in accordance with the change of allocation ratio of confined policy intervention (unit: %)

PT commuting cost subsidy + additional parking fee												
Parking (%)		0	10	20	30	40	50	60	70	80	90	100
Subsidy (%)		100	90	80	70	60	50	40	30	20	10	0
Model A2												
Net modal shift synergy effect	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0	-0.05	-0.09	-0.12	-0.13	-0.14	-0.13	-0.11	-0.09	-0.05	0
	2,000 won	0	-0.20	-0.36	-0.48	-0.55	-0.57	-0.55	-0.48	-0.37	-0.21	0
	3,000 won	0	-0.46	-0.82	-1.07	-1.23	-1.28	-1.23	-1.08	-0.82	-0.46	0
	4,000 won	0	-0.77	-1.37	-1.80	-2.07	-2.16	-2.07	-1.81	-1.38	-0.78	0
	5,000 won	0	-1.08	-1.94	-2.56	-2.94	**-3.07**	-2.95	-2.58	-1.96	-1.10	0
	6,000 won	0	-1.34	-2.43	-3.31	-3.72	-3.89	-3.74	-3.26	-2.46	-1.37	0
Model B2												
Net modal shift synergy effect	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0	-0.04	-0.08	-0.10	-0.11	-0.12	-0.11	-0.10	-0.08	-0.04	0
	2,000 won	0	-0.16	-0.29	-0.38	-0.43	-0.45	-0.43	-0.37	-0.28	-0.16	0
	3,000 won	0	-0.34	-0.61	-0.80	-0.90	-0.93	-0.89	-0.77	-0.58	-0.32	0
	4,000 won	0	-0.57	-1.00	-1.29	-1.46	-1.49	-1.41	-1.21	-0.90	-0.49	0
	5,000 won	0	-0.81	-1.41	-1.82	-2.03	**-2.06**	-1.92	-1.62	-1.19	-0.64	0
	6,000 won	0	-1.05	-1.82	-2.33	-2.57	-2.58	-2.37	-1.97	-1.41	-0.74	0

PT commuting cost subsidy + congestion charge												
Congestion (%)		0	10	20	30	40	50	60	70	80	90	100
Subsidy (%)		100	90	80	70	60	50	40	30	20	10	0
Model A2												
Net modal shift synergy effect	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0	-0.05	-0.09	-0.12	-0.13	-0.14	-0.13	-0.11	-0.08	-0.04	0
	2,000 won	0	-0.35	-0.47	-0.55	-0.58	-0.56	-0.50	-0.40	-0.25	-0.06	0
	3,000 won	0	-0.45	-0.80	-1.05	-1.20	-1.25	-1.20	-1.05	-0.80	-0.45	0
	4,000 won	0	-0.75	-1.34	-1.77	-2.02	-2.10	-2.02	-1.76	-1.34	-0.75	0
	5,000 won	0	-1.06	-1.89	-2.50	-2.86	**-2.98**	-2.85	-2.49	-1.88	-1.05	0
	6,000 won	0	-1.31	-2.37	-3.13	-3.60	-3.75	-3.59	-3.12	-2.35	-1.30	0
Model B2												
Net modal shift synergy effect	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0	-0.04	-0.07	-0.10	-0.11	-0.12	-0.12	-0.10	-0.08	-0.05	0
	2,000 won	0	-0.17	-0.29	-0.38	-0.43	-0.45	-0.43	-0.37	-0.28	-0.16	0
	3,000 won	0	-0.34	-0.61	-0.79	-0.90	-0.92	-0.88	-0.76	-0.57	-0.32	0
	4,000 won	0	-0.56	-0.98	-1.27	-1.42	-1.46	-1.37	-1.17	-0.87	-0.47	0
	5,000 won	0	-0.79	-1.38	-1.76	-1.96	**-1.98**	-1.83	-1.53	-1.11	-0.59	0
	6,000 won	0	-1.02	-1.76	-2.23	-2.45	-2.43	-2.22	-1.82	-1.29	-0.67	0

Additional parking fee + congestion charge												
Congestion (%)		0	10	20	30	40	50	60	70	80	90	100
Parking (%)		100	90	80	70	60	50	40	30	20	10	0
Model A2												
Net modal shift synergy effect	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0	-0.06	-0.10	-0.13	-0.14	-0.15	-0.14	-0.12	-0.09	-0.05	0
	2,000 won	0	-0.22	-0.39	-0.52	-0.59	-0.61	-0.59	-0.52	-0.39	-0.22	0
	3,000 won	0	-0.49	-0.88	-1.15	-1.32	-1.37	-1.32	-1.15	-0.87	-0.49	0
	4,000 won	0	-0.82	-1.47	-1.94	-2.22	-2.31	-2.21	-1.93	-1.47	-0.82	0
	5,000 won	0	-1.17	-2.09	-2.76	-3.16	**-3.29**	-3.15	-2.74	-2.07	-1.15	0
	6,000 won	0	-1.47	-2.64	-3.49	-4.00	-4.17	-3.74	-2.97	-1.87	-0.48	0
Model B2												
Net modal shift synergy effect	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0	-0.05	-0.09	-0.11	-0.13	-0.13	-0.13	-0.11	-0.08	-0.04	0
	2,000 won	0	-0.19	-0.34	-0.44	-0.50	-0.52	-0.50	-0.44	-0.33	-0.19	0
	3,000 won	0	-0.39	-0.70	-0.92	-1.05	-1.10	-1.05	-0.92	-0.70	-0.39	0
	4,000 won	0	-0.63	-1.12	-1.47	-1.68	-1.75	-1.67	-1.46	-1.10	-0.61	0
	5,000 won	0	-0.85	-1.51	-1.99	-2.28	**-2.37**	-2.27	-1.97	-1.48	-0.82	0
	6,000 won	0	-1.02	-1.83	-2.42	-2.78	-2.88	-2.52	-1.93	-1.10	-0.08	0
Model C2												
Net modal shift synergy effect	0 won	0	0	0	0	0	0	0	0	0	0	0
	1,000 won	0	-0.05	-0.09	-0.12	-0.14	-0.15	-0.14	-0.12	-0.09	-0.05	0
	2,000 won	0	-0.21	-0.38	-0.49	-0.56	-0.59	-0.56	-0.49	-0.37	-0.21	0
	3,000 won	0	-0.46	-0.81	-1.07	-1.22	-1.27	-1.22	-1.06	-0.81	-0.45	0
	4,000 won	0	-0.75	-1.33	-1.75	-2.01	-2.09	-2.01	-1.75	-1.33	-0.74	0
	5,000 won	0	-1.04	-1.86	-2.46	-2.82	**-2.94**	-2.82	-2.46	-1.86	-1.03	0
	6,000 won	0	-1.29	-2.33	-3.10	-3.56	-3.72	-3.56	-3.09	-2.33	-1.28	0

* For reference: ₩1,000 = £0.56, ₩2,000 = £1.11, ₩3,000 = £1.67, ₩4,000 = £2.22, ₩5,000 = £2.78, ₩6,000 = £3.33 (Suppose £1 = ₩1,800 (KRW, won))

6.4.3. Review of the modal shift synergy effect under the various combinations of policy intervention

In **Table 6-8**, the net modal shift synergy effects of the combined MSPs in accordance with the magnitude of the policy intervention are represented. (A) shows the market share of PT for two combined MSPs whereas (B) illustrates the average values of the market share of PT for the two individual MSPs. In addition, (C) denotes difference values between (A) and (B), while (E) shows difference values between them (C) subtracted by the average deviations (D). These difference values (E) mean the net modal shift synergy effects of the combined MSPs. That is, the differences between 'the market share of PT for an individual MSP' and 'that of the combined MSPs excluding the deviations derived from the use of the average values' are shown in **Table 6-8** (E). For reference, (A) in **Table 6-8** is expressed as the graphs in **Figure 6-11**. In addition, (E) in **Table 6-8** is expressed as the graphs in **Figure 6-12**. As shown in **Figure 6-12**, model A2 shows that the net modal shift synergy effects between PT commuting cost subsidies and additional parking fees have negative results.

Table 6-8. The modal shift synergy effects of the combined implementation between PT commuting cost subsidies and additional parking fees in model A2 (unit: %)

Calculation process	Subsidy / Parking	0 won	500 won	1000 won	1500 won	2000 won	2500 won	3000 won
Market share of PT use of combined MSPs (A)	0 won	32.45	36.10	39.92	43.87	47.89	51.95	55.98
	500 won	36.02	39.70	43.50	47.37	51.28	55.18	59.01
	1,000 won	39.75	43.41	47.14	50.90	54.66	58.36	61.97
	1,500 won	43.60	47.19	50.81	54.42	57.99	61.48	64.85
	2,000 won	47.53	51.01	54.47	57.90	61.25	64.50	67.62
	2,500 won	51.49	54.81	58.09	61.30	64.42	67.41	70.28
	3,000 won	55.43	58.56	61.62	64.59	67.46	70.20	72.80
Market share of PT of individual a PT commuting cost subsidy alone (a)	0 won	32.45	36.10	39.92	43.87	47.89	51.95	55.98
	500 won	36.10	39.92	43.87	47.89	51.95	55.98	59.93
	1,000 won	39.92	43.87	47.89	51.95	55.98	59.93	63.75
	1,500 won	43.87	47.89	51.95	55.98	59.93	63.75	67.41
	2,000 won	47.89	51.95	55.98	59.93	63.75	67.41	70.87
	2,500 won	51.95	55.98	59.93	63.75	67.41	70.87	74.10
	3,000 won	55.98	59.93	63.75	67.41	70.87	74.10	77.09
Market share of PT of individual additional parking fee alone (b)	0 won	32.45	36.02	39.75	43.60	47.53	51.49	55.43
	500 won	36.02	39.75	43.60	47.53	51.49	55.43	59.30
	1,000 won	39.75	43.60	47.53	51.49	55.43	59.30	63.07
	1,500 won	43.60	47.53	51.49	55.43	59.30	63.07	66.68
	2,000 won	47.53	51.49	55.43	59.30	63.07	66.68	70.10
	2,500 won	51.49	55.43	59.30	63.07	66.68	70.10	73.31
	3,000 won	55.43	59.30	63.07	66.68	70.10	73.31	76.30
Average value of two individual MSPs (B) = (a+b)×(1/2)	0 won	32.45	36.06	39.83	43.73	47.71	51.72	55.70
	500 won	36.06	39.83	43.73	47.71	51.72	55.70	59.61
	1,000 won	39.83	43.73	47.71	51.72	55.70	59.61	63.41
	1,500 won	43.73	47.71	51.72	55.70	59.61	63.41	67.04
	2,000 won	47.71	51.72	55.70	59.61	63.41	67.04	70.48
	2,500 won	51.72	55.70	59.61	63.41	67.04	70.48	73.71
	3,000 won	55.70	59.61	63.41	67.04	70.48	73.71	76.69

Difference between values of combined MSPs and value of individual MSP (C)= A – B	0 won	0	0.04	0.09	0.14	0.18	0.23	0.27
	500 won	-0.04	-0.14	-0.24	-0.34	-0.44	-0.53	-0.61
	1,000 won	-0.09	-0.33	-0.57	-0.81	-1.04	-1.26	-1.44
	1,500 won	-0.14	-0.52	-0.91	-1.28	-1.62	-1.93	-2.20
	2,000 won	-0.18	-0.71	-1.23	-1.71	-2.16	-2.54	-2.86
	2,500 won	-0.23	-0.89	-1.52	-2.11	-2.63	-3.07	-3.43
	3,000 won	-0.27	-1.06	-1.79	-2.45	-3.03	-3.51	-3.89
Deviations from use of average values (D)	0 won	0	0.04	0.09	0.14	0.18	0.23	0.27
	500 won	-0.04	0.00	0.04	0.09	0.14	0.18	0.23
	1,000 won	-0.09	-0.04	0.00	0.05	0.09	0.14	0.18
	1,500 won	-0.14	-0.09	-0.05	0.00	0.05	0.09	0.14
	2,000 won	-0.18	-0.14	-0.09	-0.05	0.00	0.05	0.09
	2,500 won	-0.23	-0.18	-0.14	-0.09	-0.05	0.00	0.05
	3,000 won	-0.27	-0.23	-0.18	-0.14	-0.09	-0.05	0.00
Difference between them excluding deviation (E) = C – D	0 won	0	0	0	0	0	0	0
	500 won	0	-0.14	-0.28	-0.43	-0.57	-0.71	-0.84
	1,000 won	0	-0.28	-0.57	-0.86	-1.14	-1.39	-1.62
	1,500 won	0	-0.43	-0.86	-1.28	-1.67	-2.03	-2.33
	2,000 won	0	-0.57	-1.14	-1.67	-2.16	-2.59	-2.96
	2,500 won	0	-0.71	-1.39	-2.02	-2.58	**-3.07**	-3.48
	3,000 won	0	-0.83	-1.61	-2.31	-2.93	-3.46	-3.89

Figure 6-11. The modal shift probability curve of the combination between PT commuting cost subsidies and additional parking fees in model A2

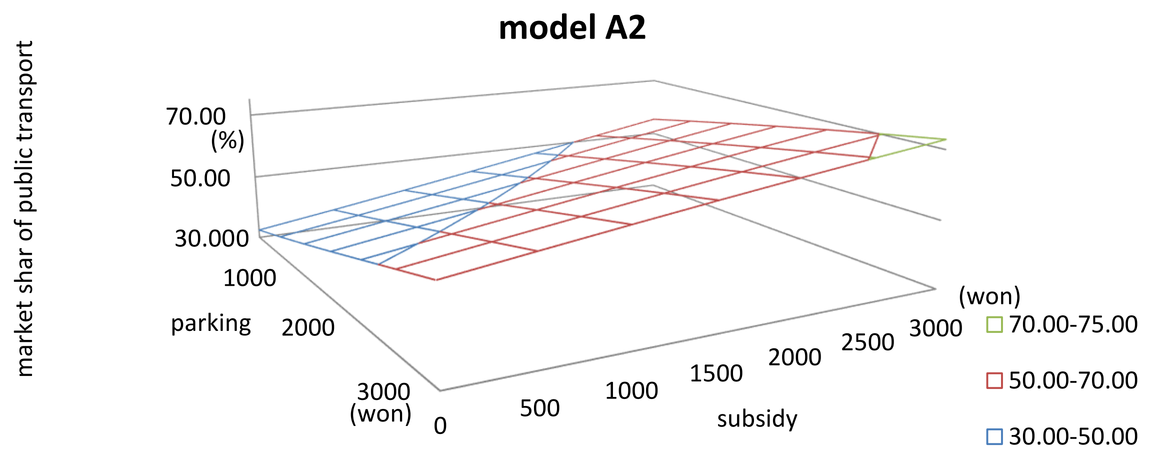


Figure 6-12. The net modal shift synergy effects of the combined MSPs (PT commuting cost subsidies and additional parking fees) in accordance with the change of policy intervention

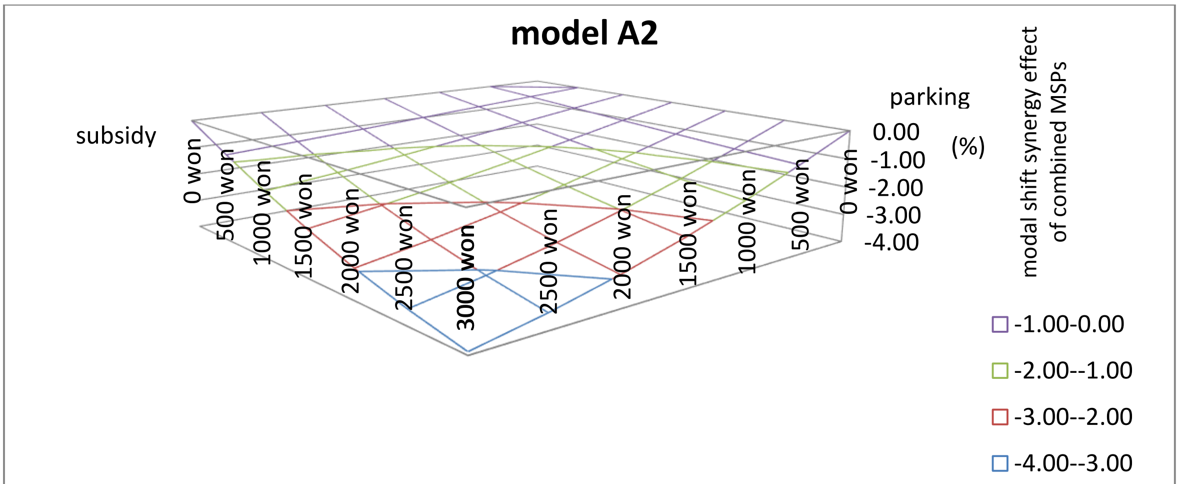


Table 6-9 shows the net modal shift synergy effects of the combined MSPs. The calculation process of net modal shift synergy effects of the combined MSPs is the same as that of **Table 6-8**. Each net modal shift synergy effects of each combined MSPs in **Table 6-9** can be expressed as the graphs like **Figure 6-12**. Although there is a little difference of the magnitude of the net modal shift synergy effects, all the forms of the graphs are similar to **Figure 6-12**.

Table 6-9. The net modal shift synergy effects of the combined MSPs in accordance with the change of the magnitude of policy intervention (unit: %)

PT commuting cost subsidy + additional parking fee								
	Subsidy / Parking	0 won	500 won	1,000 won	1,500 won	2,000 won	2,500 won	3,000 won
Model A2	0 won	0	0	0	0	0	0	0
	500 won	0	-0.14	-0.28	-0.43	-0.57	-0.71	-0.84
	1,000 won	0	-0.28	-0.57	-0.86	-1.14	-1.39	-1.62
	1,500 won	0	-0.43	-0.86	-1.28	-1.67	-2.03	-2.33
	2,000 won	0	-0.57	-1.14	-1.67	-2.16	-2.59	-2.96
	2,500 won	0	-0.71	-1.39	-2.02	-2.58	**-3.07**	-3.48
	3,000 won	0	-0.83	-1.61	-2.31	-2.93	-3.46	-3.89
Model B2	0 won	0	0	0	0	0	0	0
	500 won	0	-0.12	-0.23	-0.33	-0.41	-0.47	-0.51
	1,000 won	0	-0.23	-0.45	-0.64	-0.79	-0.90	-0.98
	1,500 won	0	-0.34	-0.66	-0.93	-1.15	-1.31	-1.42
	2,000 won	0	-0.46	-0.87	-1.22	-1.49	-1.69	-1.82
	2,500 won	0	-0.56	-1.07	-1.49	-1.82	**-2.06**	-2.21
	3,000 won	0	-0.66	-1.25	-1.74	-2.13	-2.41	-2.58

PT commuting cost subsidy + congestion charge								
	Subsidy / Congestion	0 won	500 won	1,000 won	1,500 won	2,000 won	2,500 won	3,000 won
Model A2	0 won	0	0	0	0	0	0	0
	500 won	0	-0.14	-0.28	-0.42	-0.56	-0.69	-0.81
	1,000 won	0	-0.28	-0.56	-0.84	-1.11	-1.36	-1.57
	1,500 won	0	-0.42	-0.84	-1.25	-1.63	-1.97	-2.25
	2,000 won	0	-0.56	-1.11	-1.63	-2.10	-2.51	-2.85
	2,500 won	0	-0.70	-1.36	-1.97	-2.52	**-2.98**	-3.35
	3,000 won	0	-0.82	-1.58	-2.26	-2.86	-3.36	-3.75
Model B2	0 won	0	0	0	0	0	0	0
	500 won	0	-0.12	-0.23	-0.33	-0.40	-0.45	-0.49
	1,000 won	0	-0.23	-0.45	-0.63	-0.77	-0.87	-0.93
	1,500 won	0	-0.35	-0.66	-0.92	-1.12	-1.25	-1.33
	2,000 won	0	-0.46	-0.87	-1.21	-1.46	-1.62	-1.71
	2,500 won	0	-0.57	-1.06	-1.47	-1.78	**-1.98**	-2.08
	3,000 won	0	-0.67	-1.24	-1.71	-2.07	-2.31	-2.43

Additional parking fee + congestion charge								
	Parking / Congestion	0 won	500 won	1,000 won	1,500 won	2,000 won	2,500 won	3,000 won
Model A2	0 won	0	0	0	0	0	0	0
	500 won	0	-0.15	-0.30	-0.46	-0.62	-0.69	-0.89
	1,000 won	0	-0.30	-0.61	-0.92	-1.22	-1.41	-1.72
	1,500 won	0	-0.46	-0.92	-1.37	-1.79	-2.09	-2.47
	2,000 won	0	-0.62	-1.22	-1.79	-2.31	-2.69	-3.14
	2,500 won	0	-0.83	-1.56	-2.24	-2.84	**-3.29**	-3.70
	3,000 won	0	-0.90	-1.74	-2.50	-3.17	-3.72	-4.17

Model B2	0 won	0	0	0	0	0	0	0
	500 won	0	-0.13	-0.26	-0.39	-0.50	-0.60	-0.68
	1,000 won	0	-0.27	-0.52	-0.76	-0.96	-1.14	-1.28
	1,500 won	0	-0.39	-0.76	-1.10	-1.38	-1.62	-1.80
	2,000 won	0	-0.51	-0.99	-1.40	-1.75	-2.03	-2.25
	2,500 won	0	-0.62	-1.17	-1.66	-2.06	**-2.37**	-2.60
	3,000 won	0	-0.71	-1.33	-1.87	-2.30	-2.65	-2.88
Model C2	0 won	0	0	0	0	0	0	0
	500 won	0	-0.15	-0.30	-0.44	-0.58	-0.71	-0.82
	1,000 won	0	-0.29	-0.59	-0.87	-1.13	-1.36	-1.57
	1,500 won	0	-0.44	-0.87	-1.27	-1.64	-1.96	-2.24
	2,000 won	0	-0.58	-1.13	-1.64	-2.09	-2.49	-2.82
	2,500 won	0	-0.70	-1.36	-1.96	-2.49	**-2.94**	-3.32
	3,000 won	0	-0.81	-1.56	-2.23	-2.82	-3.32	-3.72

* The values of blue coloured cell in **Table 6-9** corresponds to the values of blue coloured cell in **Table 6-7**

* Reference: ₩1,000 = £0.56, ₩2,000 = £1.11, ₩3,000 = £1.67, ₩4,000 = £2.22, ₩5,000 = £2.78, ₩6,000 = £3.33 (Suppose £1 = ₩1,800(KRW, won))

In the case of a model with no statistically significant coefficients related to interaction effects, the value of the net modal shift synergy effect should be zero. However, according to the result of the analysis, its values have the positive values even though the magnitude of value is small. The consistent positive values may be derived from the S-shaped logit curve or the deviations of logit models unknown to the public. The detailed result of the analysis is attached to **Appendix 6**.

Considering the positive values derived from a model with no statistically significant coefficients, the negative net modal shift synergy effect may be bigger than the figures of **Table 6-9**. However, the magnitude of additional negative net modal shift synergy effect will be small.

6.4.4. Discrepancy of the modal shift synergy effect

Through the second method (see **Figure 6-8**), another value of the modal shift synergy effect can be calculated. That is, since each modal shift probability of policy A alone or policy B alone (e.g. policy intervention at the level of 2,500 won respectively) can be calculated, the sum of these values would be obtained. The discrepancy between 'the simple sum [(D) in **Table 6-10**] of the modal shift probability for policy A alone (A) and policy B alone (B)' and 'the estimated value (H) of modal shift probability for the combination of policy A and policy B' can be also regarded as 'the modal shift synergy effect' (I). Its value (I) is different from the value (J) of 'the net modal shift synergy effect' obtained from the first method. That is, the net modal shift synergy effect by using the first method is derived from the differences (J) between 'the estimated value (H) of the modal shift probability for the combined MSPs' and 'the average value (G) of the sum of the modal shift probability for each MSP alone (E and F) (e.g. policy intervention at the level of 5,000 won)'.

What is the reason for the differences (K) of the modal shift probability between (I) and (J) in **Table 6-10**? Although the cause is not clearly known yet, the difference in the magnitude of the marginal modal shift probability (see **Table 5-3**) can be a possible cause. Since the signs of the values are changed around the maximum points of marginal modal shift probability, the difference of the magnitude of policy intervention (e.g. 2,500 won : 5,000 won) applied by the two methods may account for the differences. For example, the degree of the application of the diminishing law for the marginal modal shift probability of policy A at the level of 2,500 won is different from that of 5,000 won [compare the maximum points in **Table 5-3** with the values of (K) in **Table 6-10**]. Another possible reason may be derived from the S-shaped line of logit curve. On the basis of 50% of modal shift probability, a lower percentage may be more underestimated while higher percentage tends to be more overestimated rather than the utility value of travel mode. Although it can be regarded as the redundancy effect at the first glimpse, both the small magnitude of the values and the frequent change of the signs indicate that these differences [(K) in **Table 6-10**] do not seem to be the redundancy effect.

In general, the redundancy effect results from the overlapping of the modal shift effects between the combined MSPs. That is, redundancy arises where two policy interventions are directed at the same people, who are unable to change their behaviour twice (Jones and Sloman, 2003). Therefore, the redundancy effect could be the underlying cause of the occurrence of the negative modal shift synergy effect, if anything. May et al. (2004) indicates that "negative synergy effect implies that there is some obvious overlap between the cordon and parking charges". **Figure 6-13** shows the concept of the negative modal shift synergy effects is derived from the redundancy phenomenon or overlapping of policies.

In terms of the simple concept of a set,

(1) If synergy effect (S) does not exist and if intersection portion (A⋂B) does not exist, 'the magnitude of the combination of policy A and policy B (A⋃B)' is equal to 'the sum of policy A alone and policy B alone (A+B)': [if S = 0 & A⋂B = 0 → A⋃B = A+B]

(2) If synergy effect (S) exists and if intersection portion (A⋂B) does not exist, 'the magnitude of the combination of policy A and policy B (A⋃B)' is greater than 'the sum of policy A alone and policy B alone (A+B)': [if S ≠ 0 & A⋂B = 0 → A⋃B 〉 A+B].

(3) If synergy effect (S) does not exist and if intersection portion (A⋂B) exists, 'the magnitude of the combination of policy A and policy B (A⋃B)' is smaller than 'the sum of policy A alone and policy B alone (A+B)': [if S = 0 & A⋂B ≠ 0 → A⋃B 〈 A+B].

(4) If synergy effect (S) exists and if intersection portion (A⋂B) exists, apart from the case that the magnitude of synergy effect (S) equals the magnitude of intersection portion (A⋂B), what synergy effect occurs, either positive or negative, depends on 'the magnitude of the combination of policy A and policy B (A⋃B)' and 'the sum of policy A alone and policy B alone (A+B)': [if S ≠ 0 & A⋂B ≠ 0 (& S ≠ A⋂B) → 'A⋃B 〈 A+B' or 'A⋃B 〉 A+B'].

The difference between 'the magnitude of the combination of policy A and policy B (A⋃B)' and 'the sum of policy A alone and policy B alone (A+B)' generally depends on 'the magnitude of intersection portion (A⋂B)'. As a result, what synergy effect occurs, either positive or negative, depends on 'the magnitude of intersection portion (A⋂B)'.

(4-1) In this case, if 'the magnitude of the intersection portion (A⋂B)' is smaller than 'the magnitude of synergy effect (S)', the positive synergy effect will occur.
On the contrary, (4-2) 'the magnitude of the intersection portion (A⋂B)' is greater than 'the magnitude of synergy effect (S)', the negative synergy effect will occur.

In **Figure 6-13**, if 'the magnitude of the intersection portion (A⋂B)' is large enough to outweigh 'the magnitude of the positive synergy effect (S)', the negative modal shift synergy effect will occur. Conversely, 'the magnitude of the positive synergy effect (S)' is large enough to be greater than 'the magnitude of the intersection portion (A⋂B)', a positive modal shift synergy effect will occur.

In this case, the intersection portion (A⋂B) may ultimately come from the similarity of the type or characteristics of policies. If there are lots of transport policies whose the objective, intention, means, characteristics, and so on is similar, the redundancy of transport policies may occur.

In this study, since the three MSPs are directly related to economic instruments, the redundancy effect may be larger than other MSPs with different policy instruments. That is, these policies are pricing-focused policies and one of the most effective transport policies with the same or similar objectives. In particular, the negative synergy effect between push measures is greater than the one between a pull measure and a push measure in this research (see **Table 6-11**). That is, the effect from the combination of the PT commuting cost subsidy and congestion charging would make a smaller amount of the negative synergy effect than the one from a bond of the parking fee and congestion charging. Therefore, it can be inferred that the negative modal shift synergy effect comes from a larger magnitude of modal shift redundancy effect in this research.

All in all, in terms of the basic concept, the synergy effect that is overwhelmed by the redundancy effect can appear as a negative synergy effect in reality. The larger the overlapping part, the greater the potential for the manifestation of a negative synergy effect. However, if policy characteristics such as the policy objectives, means and characteristics are different from each other, the occurrence of redundancy phenomenon will be decreased. Thus, the less the overlapping part, the greater the potential for the manifestation of a positive synergy effect.

In the real world, the occurrence of a negative synergy effect may be common rather than a positive synergy effect since significant overlapping between the two policies exists in many cases. Although this research explains the relationship between 'modal shift synergy effect' and 'redundancy effect' in terms of the concept of a set, more research on the fundamental elements of policy characteristics is needed.

Figure 6-13. The concept of negative modal shift synergy effect and redundancy phenomenon

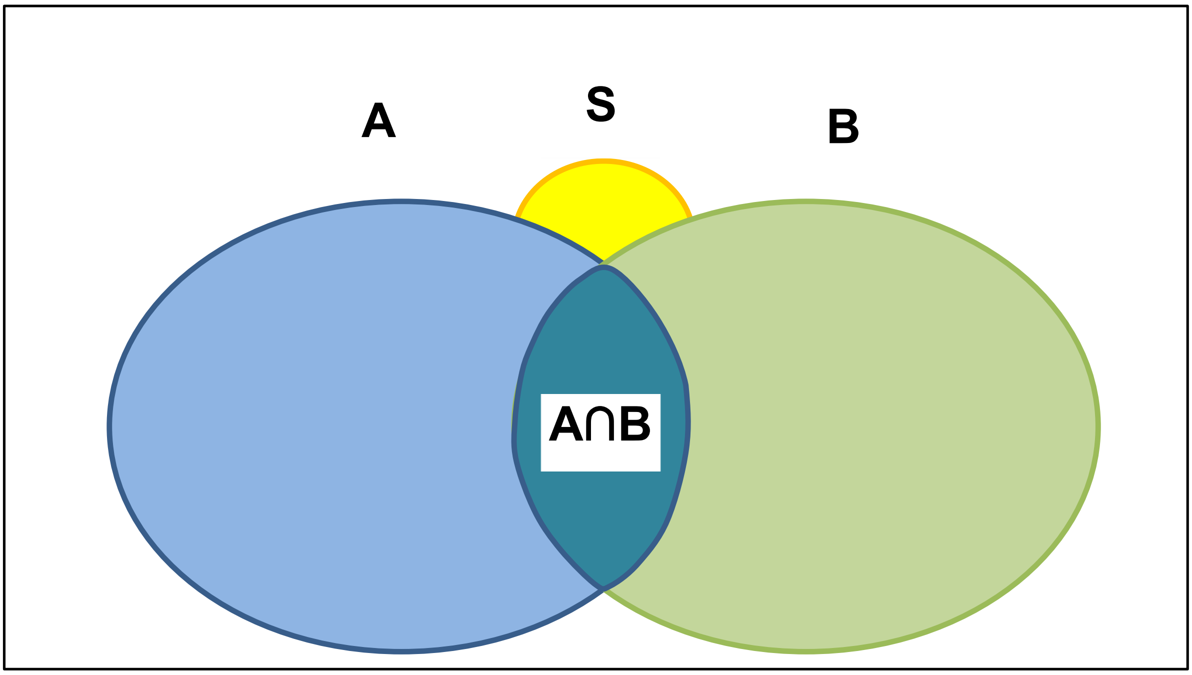


Table 6-10 shows the numerical figures of 'the modal shift synergy effect' calculated by using the second method and 'the net modal shift effect' calculated by using the first method. Overall, at the low level of policy intervention, the degree of the modal shift synergy effect is very small whereas at the high level of policy intervention, the degree of the modal shift synergy effect is large. In practice, the real value of a modal shift synergy effect might be determined as average values between (I) and (J) in **Table 6-10**. However, for the convenience of this analysis, the concept of the net modal shift synergy effect using the first method is mainly used in this research.

Table 6-10. Calculation of the modal shift synergy effect of the combined MSPs (unit: %)

PT commuting cost subsidy + additional parking fee

Type of model	Interven-tion degree	One policy intervention				Twice policy intervention					(D)–(H) =(J)+(K) *inverse synergy ②	(G)–(H) *inverse synergy ①	(D)–(G) (②-①)
		Subsidy alone (A)	Parking alone (B)	(A)+(B) = (C)	C–0 won = (D)	Subsidy alone $(A)^{twice}$ (E)	Parking alone $(B)^{twice}$ (F)	Average value (G)	**Combined MSPs** estimated value **(H)**	Intervention Degree	= (I)	= (J)	= (K)
Model A2	0 won	32.45	32.45	64.9	**32.45**	32.45	32.45	32.45	32.45	(0 won)	0	0	0
	500 won	36.10	36.02	72.12	39.67	39.92	39.75	39.83	39.70	(1000 won)	-0.03	0.14	-0.16
	1000 won	39.92	39.75	79.67	47.22	47.89	47.53	47.71	47.14	(2000 won)	0.08	0.57	-0.49
	1500 won	43.87	43.60	87.47	55.02	55.98	55.43	55.70	54.42	(3000 won)	0.6	1.28	-0.68
	2000 won	47.89	47.53	95.42	62.97	63.75	63.07	63.41	61.25	(4000 won)	1.72	2.16	-0.44
	2500 won	51.95	51.49	103.44	70.99	70.87	70.10	70.48	67.41	(5000 won)	3.58	**3.07**	0.51
	3000 won	55.98	55.43	111.41	78.96	77.09	76.30	76.69	72.80	(6000 won)	6.16	3.89	2.27
Model B2	0 won	41.72	41.72	83.44	41.72	41.72	41.72	41.72	41.72	(0 won)	0	0	0
	500 won	44.19	45.56	89.75	48.03	46.69	49.45	48.07	47.95	(1000 won)	0.08	0.12	-0.04
	1000 won	46.69	49.45	96.14	54.42	51.72	57.20	54.46	54.01	(2000 won)	0.41	0.45	-0.04
	1500 won	49.20	53.35	102.55	60.83	56.72	64.62	60.67	59.74	(3000 won)	1.09	0.93	0.16
	2000 won	51.72	57.20	108.92	67.2	61.58	71.39	66.49	64.99	(4000 won)	2.21	1.49	0.71
	2500 won	54.23	60.97	115.2	73.48	66.23	77.32	71.77	69.71	(5000 won)	3.77	**2.06**	1.71
	3000 won	56.72	64.62	121.34	79.62	70.58	82.32	76.45	73.87	(6000 won)	5.75	2.58	3.17

PT commuting cost subsidy + congestion charge

Type of model	Interven-tion degree	One policy intervention				Twice policy intervention					(D)–(H) =(J)+(K) *inverse synergy ②	(G)–(H) *inverse synergy ①	D)–(G) (②-①)
		Subsidy Alone (A)	Parking Alone (B)	(A)+(B) = (C)	C–0 won = (D)	Subsidy alone $(A)^{twice}$ (E)	Parking alone $(B)^{twice}$ (F)	Average value (G)	**Combined MSPs** estimated value **(H)**	Intervention degree	= (I)	= (J)	= (K)
Model A2	0 won	32.45	32.45	64.9	32.45	32.45	32.45	32.45	32.45	(0 won)	0	0	0
	500 won	36.10	36.15	72.25	39.8	39.92	40.01	39.97	39.83	(1000 won)	-0.03	0.14	-0.17
	1000 won	39.92	40.01	79.93	47.48	47.89	48.08	47.99	47.43	(2000 won)	0.05	0.56	-0.51
	1500 won	43.87	44.01	87.88	55.43	55.98	56.25	56.11	54.86	(3000 won)	0.57	1.25	-0.68
	2000 won	47.89	48.08	95.97	63.52	63.75	64.10	63.92	61.82	(4000 won)	1.7	2.10	-0.40
	2500 won	51.95	52.18	104.13	71.68	70.87	71.25	71.06	68.08	(5000 won)	3.6	**2.98**	0.62
	3000 won	55.98	56.25	112.23	79.78	77.09	77.48	77.29	73.54	(6000 won)	6.24	3.75	2.49
Model B2	0 won	41.72	41.72	83.44	41.72	41.72	41.72	41.72	41.72	(0 won)	0	0	0
	500 won	44.19	45.72	89.91	48.19	46.69	49.78	48.23	48.12	(1000 won)	0.07	0.12	-0.04
	1000 won	46.69	49.78	96.47	54.75	51.72	57.85	54.78	54.33	(2000 won)	0.42	0.45	-0.03
	1500 won	49.20	53.84	103.04	61.32	56.72	65.52	61.12	60.19	(3000 won)	1.13	0.92	0.20
	2000 won	51.72	57.85	109.57	67.85	61.58	72.45	67.02	65.56	(4000 won)	2.29	1.46	0.83
	2500 won	54.23	61.75	115.98	74.26	66.23	78.46	72.34	70.37	(5000 won)	3.89	**1.98**	1.92
	3000 won	56.72	65.52	122.24	80.52	70.58	83.45	77.01	74.58	(6000 won)	5.94	2.43	3.51

Additional parking fee + congestion charge

Type of model	Interven-tion degree	One policy intervention				Twice policy intervention					(D)–(H) =(J)+(K) *inverse synergy ②	(G)–(H) *inverse synergy ①	D)–(G) (②-①)
		Parking Alone (A)	Congestion Alone (B)	(A)+(B) = (C)	C–0 won = (D)	Subsidy alone $(A)^{twice}$ (E)	Parking alone $(B)^{twice}$ (F)	Average value (G)	**Combined MSPs** estimated value **(H)**	Intervention degree	= (I)	= (J)	= (K)
Model A2	0 won	32.45	32.45	64.9	32.45	32.45	32.45	32.45	32.45	(0 won)	0	0	0
	500 won	36.02	36.15	72.17	39.72	39.75	40.01	39.88	39.73	(1000 won)	-0.01	0.15	-0.16
	1000 won	39.75	40.01	79.76	47.31	47.53	48.08	47.80	47.19	(2000 won)	0.12	0.61	-0.49
	1500 won	43.60	44.01	87.61	55.16	55.43	56.25	55.84	54.47	(3000 won)	0.69	1.37	-0.68
	2000 won	47.53	48.08	95.61	63.16	63.07	64.10	63.58	61.27	(4000 won)	1.89	2.31	-0.42
	2500 won	51.49	52.18	103.67	71.22	70.10	71.25	70.68	67.39	(5000 won)	3.83	**3.29**	0.54
	3000 won	55.43	56.25	111.68	79.23	76.30	77.48	76.89	72.73	(6000 won)	6.5	4.17	2.34
Model B2	0 won	41.72	41.72	83.44	41.72	41.72	41.72	41.72	41.72	(0 won)	0	0	0
	500 won	45.56	45.72	91.28	49.56	49.45	49.78	49.62	49.48	(1000 won)	0.08	0.13	-0.06
	1000 won	49.45	49.78	99.23	57.51	57.20	57.85	57.52	57.00	(2000 won)	0.51	0.52	-0.01
	1500 won	53.35	53.84	107.19	65.47	64.62	65.52	65.07	63.97	(3000 won)	1.5	1.10	0.40
	2000 won	57.20	57.85	115.05	73.33	71.39	72.45	71.92	70.17	(4000 won)	3.16	1.75	1.41
	2500 won	60.97	61.75	122.72	81	77.32	78.46	77.89	75.52	(5000 won)	5.48	**2.37**	3.11
	3000 won	64.62	65.52	130.14	88.42	82.32	83.45	82.89	80.00	(6000 won)	8.42	2.88	5.53
Model C2	0 won	39.62	39.62	79.24	39.62	39.62	39.62	39.62	39.62	(0 won)	0	0	0
	500 won	43.17	43.17	86.34	46.72	46.79	46.80	46.80	46.65	(1000 won)	0.07	0.15	-0.08
	1000 won	46.79	46.80	93.59	53.97	54.10	54.10	54.10	53.52	(2000 won)	0.45	0.59	-0.13
	1500 won	50.45	50.45	100.9	61.28	61.23	61.24	61.24	59.97	(3000 won)	1.31	1.27	0.04
	2000 won	54.10	54.10	108.2	68.58	67.92	67.93	67.92	65.83	(4000 won)	2.75	2.09	0.66
	2500 won	57.71	57.71	115.42	75.8	73.94	73.95	73.94	71.00	(5000 won)	4.8	2.94	1.86
	3000 won	61.23	61.24	122.47	82.85	79.18	79.18	79.18	75.46	(6000 won)	7.39	3.72	3.67

* **Table 6-10** corresponds to **Figure 6-8**.

* Column (G) = $\frac{(A)^{twice} + (B)^{twice}}{2}$

* Column (J) implies the net modal shift synergy effect (see **Table 6-10**) calculated by using the first method [= (G) – (H)].

* Column (I) denotes the modal shift effect calculated by using the first method [= (D) – (H) = (J) + (K)].

* Column (K) denotes the difference between (I) and (J) [= (I) – (J) = (D) – (G)].

* 0 won means no policy intervention.

6.4.5. What combination of modal shift policies is the most powerful modal shift synergy effects?

The thesis on modal shift synergy effect gives many implications as follows: First, all the combinations of the two MSPs, as the combinations of both pricing transport policies, make negative modal shift synergy effects according to the change of allocation ratio of policy intervention (see **Table 6-11**). In other words, if there is an interaction effect between the two MSPs, the integration of the two MSPs creates a negative effect in terms of modal shift effect.

Second, the greatest level of negative modal shift synergy effects would be created by the combination of additional parking fees and congestion charges, with the bond of PT commuting cost subsidies and additional parking fees the next greatest, and the lowest level of negative modal shift synergy effects gained by the union of PT commuting cost subsidies and congestion charges. As a result, in terms of the modal shift synergy effects, the integration of PT commuting cost subsidies and congestion charges is the best combination since this combination results in the least negative net modal shift synergy effects out of the three combinations. Conversely, the worst combination is the combination of additional parking fees and congestion charges due to the maximum minus values. Unlike the market share estimates of the transport mode, which depends on the type of models (see **Figure 5-2** and orange coloured cell in **Table 5-2**), the order of the modal shift synergy effect is always the same regardless of the type of models (see **Table 6-11**).

Table 6-11. The net modal shift synergy effect of the combined MSPs in accordance with the change of allocation ratio of policy intervention (5,000 won) (unit: %)

Allocation ratio of MSP	0	10	20	30	40	50	60	70	80	90	100
	100	90	80	70	60	50	40	30	20	10	0
Model A2											
Subsidy & Parking	0	-1.08	-1.94	-2.56	-2.94	**-3.07**	-2.95	-2.58	-1.96	-1.10	0
Subsidy & Congestion	0	-1.06	-1.89	-2.50	-2.86	**-2.98**	-2.85	-2.49	-1.88	-1.05	0
Parking & Congestion	0	-1.17	-2.09	-2.76	-3.16	**-3.29**	-3.15	-2.74	-2.07	-1.15	0
Model B2											
Subsidy & Parking	0	-0.81	-1.41	-1.82	-2.03	**-2.06**	-1.92	-1.62	-1.19	-0.64	0
Subsidy & Congestion	0	-0.79	-1.38	-1.76	-1.96	**-1.98**	-1.83	-1.53	-1.11	-0.59	0
Parking & Congestion	0	-0.85	-1.51	-1.99	-2.28	**-2.37**	-2.27	-1.97	-1.48	-0.82	0

* These values correspond to the values of **Table 6-7** and **Table 6-9**.

Third, although the discrepancy between the modal shift synergy effects is small, negative modal shift synergy effects between a push measure and a push measure (e.g. additional parking fee & congestion charge – 3.29) are bigger than the ones between a pull measure and a push measure (e.g. PT commuting cost subsidy & additional parking fee – 3.07). That is, the combination of a pull measure and a push measure seems to create less negative result than the bond of a push measure and a push measure.

Fourth, the negative modal shift synergy effects seem to come from the combination of the hard measure and the hard measure. However, this result does not mean that all the combination of transport policies may create negative modal shift synergy effects. Jones and Sloman (2003) argue that, by combining the introduction of road user charging with a target information and marketing campaign, it would be possible to achieve desirable results. That is, Jones and Sloman indicate that the combination of a hard measure and a soft measure may make positive synergy effect. Soft measures can pave the way for the introduction of the hard measures. A soft measure is related to nudges that are not sufficient alone but needed to form part of intervention packages. Therefore, this study just indicates that the combination of a hard measure and a hard measure may lead to the negative modal shift synergy effect. This result seems to induce that in terms of policy characteristics, policy package comprising the same type of policy makes the negative synergy effect. Therefore, policy package combined by different types of policy such as economic measures, regulatory measures, informative measures, educational measures and other soft measures may construct the positive result. However, the development of the same or similar condition for comparing the different types of the policy may be very difficult, in practice. However, these results may offer good evidence and new insight about the modal shift synergy effects in the aspect of policy packaging.

Fifth, the effectiveness of the push measures (sticks) for reducing car use seems to be higher than the pull measures (carrots) (O'Fallon et al., 2004). At the same monetary level of economic support or levy limitation (5,000 won, £2.78), congestion charges obtain the highest level of the market share of PT regardless of the type of models (see **Table 6-11**). In terms of modal shift effectiveness for prompting mode changes, congestion charges are the most effective MSP. In the case of model A2 made up of only the SP data (level unit), the effectiveness of PT commuting cost subsidies (70.87%) is higher than additional parking fees (70.10%) (see **Table 6-12**). However, in the case of model B2 and model C2 composed of SP data and RP data (monetary unit), the effectiveness of PT commuting cost subsidies (pull measures) for modal shift is lower than additional parking fees (push measures). Overall, this research indicates that the effectiveness of the push measure is higher than the pull measure.

Table 6-12. The market share of PT when the individual MSP is implemented at the same monetary level of policy intervention (5,000 won)

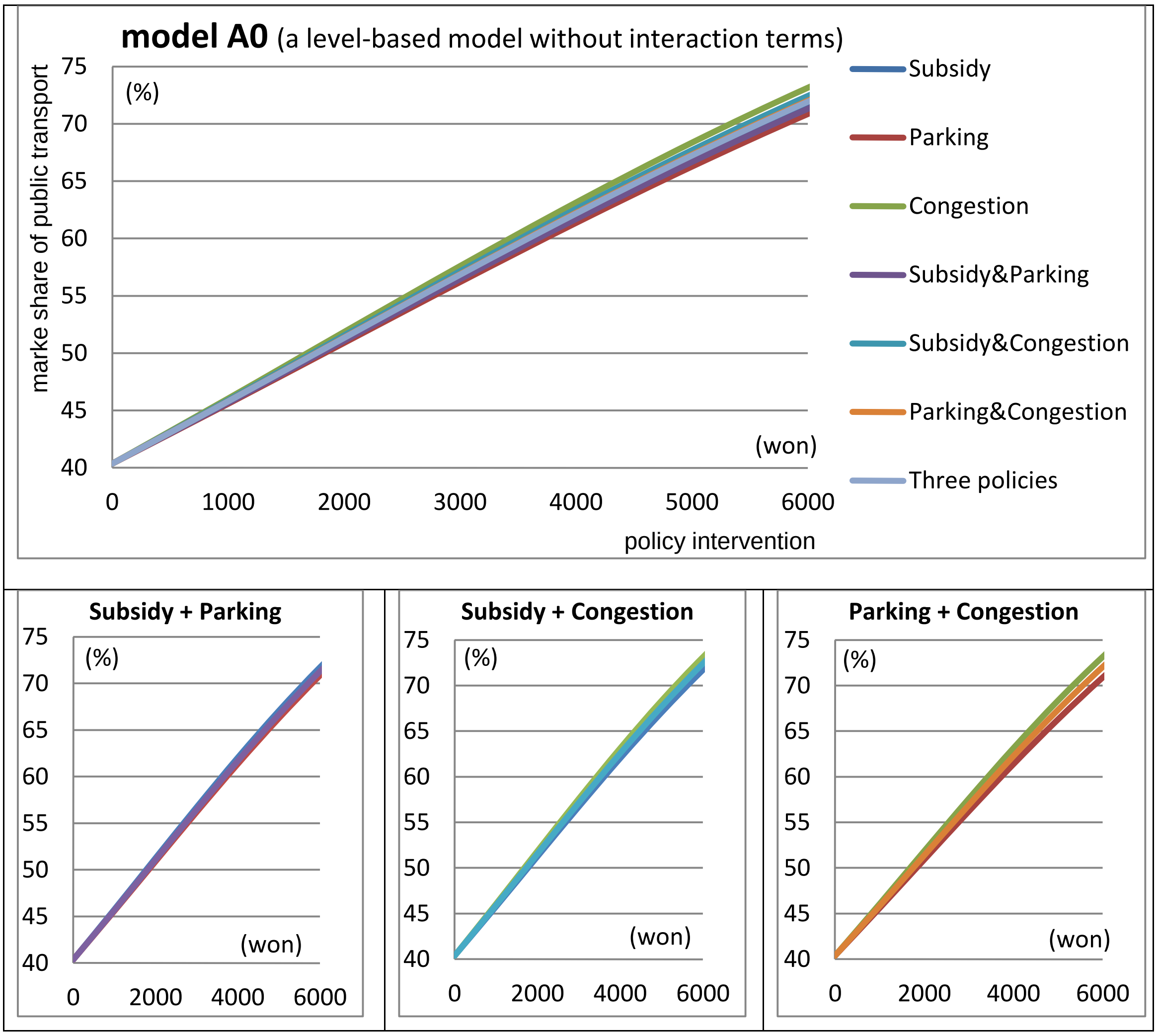
Input value (5,000 won = £2.78)			Type of model	Model A2	Model B2	Model C2
PT subsidy	Parking fee	Congestion charge				
5,000 won	0	0	Market share of PT	70.87%	66.23%	55.51%
0	5,000 won	0		70.10%	77.32%	73.94%
0	0	5,000 won		**71.25%**	**78.46%**	**73.95%**

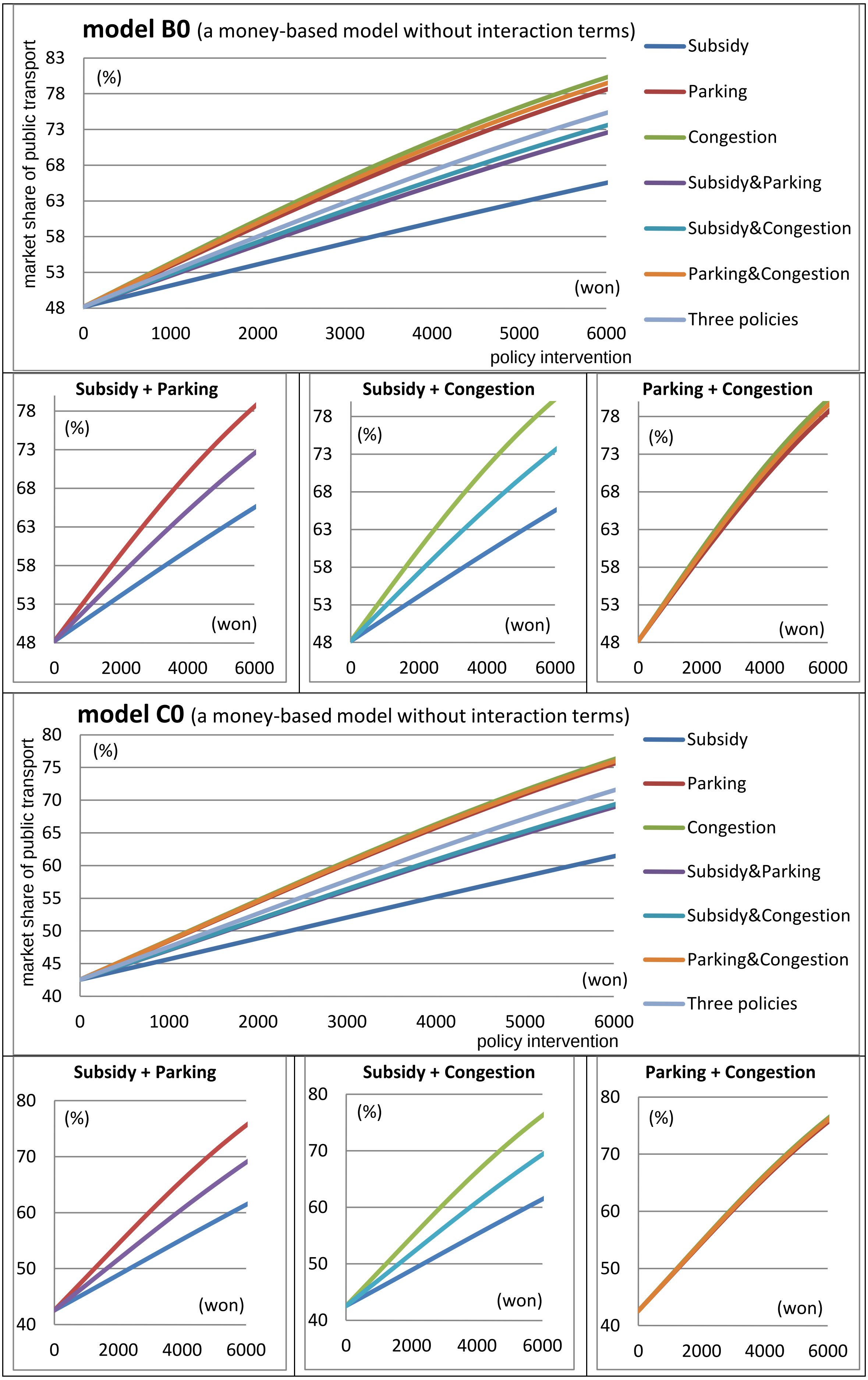
6.5. Difference of the Modal Shift Probability Curves between the Models without and with Interaction Terms

6.5.1. Review of interactions in models 0

Figure 6-14 compares the market share of PT in models 0, which are models without interaction terms (i.e. model A0, B0, and C0), at the same monetary level of policy intervention. The values of the market share of PT seem to be settled as intermediate values between those of individual MSPs. That is, since there are no coefficients related to interaction effects, the market share of PT is an approximate average value of each MSP. This result indicates that there are no interaction effects beyond the simple sum of individual MSPs. In conclusion, since there are no interaction effects, the market share of PT for the combined MSPs seems to be an average value of each single MSP. In this case, there is no modal shift synergy effect.

Figure 6-14. The market share of PT of the combined MSPs in models 0 at the same monetary level of policy intervention




model B0 (a money-based model without interaction terms)
market share of public transport
(%)
83
78
73
68
63
58
53
48
0
1000
2000
3000
4000
5000
6000
(won)
policy intervention
Subsidy
Parking
Congestion
Subsidy&Parking
Subsidy&Congestion
Parking&Congestion
Three policies
Subsidy + Parking
Subsidy + Congestion
Parking + Congestion
model C0 (a money-based model without interaction terms)
80
75
70
65
60
55
50
45
40

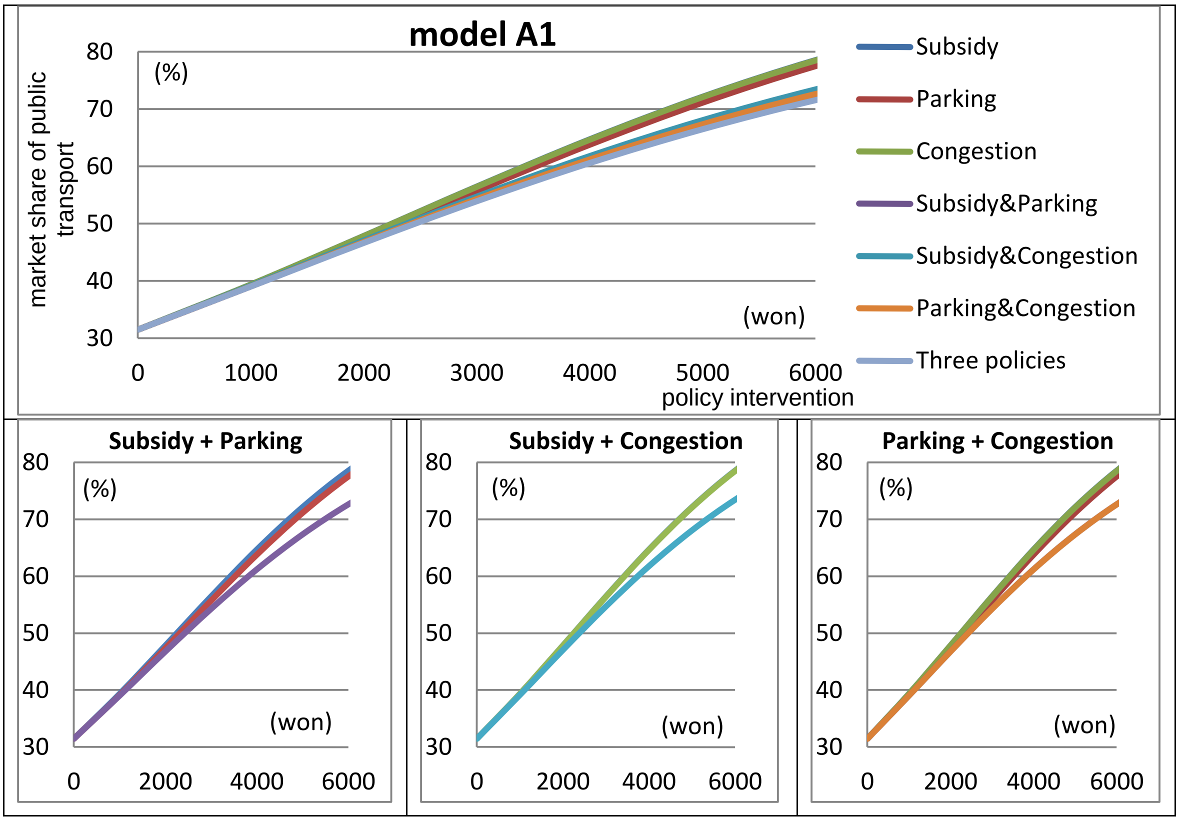
6.5.2. Review of interactions in models 1

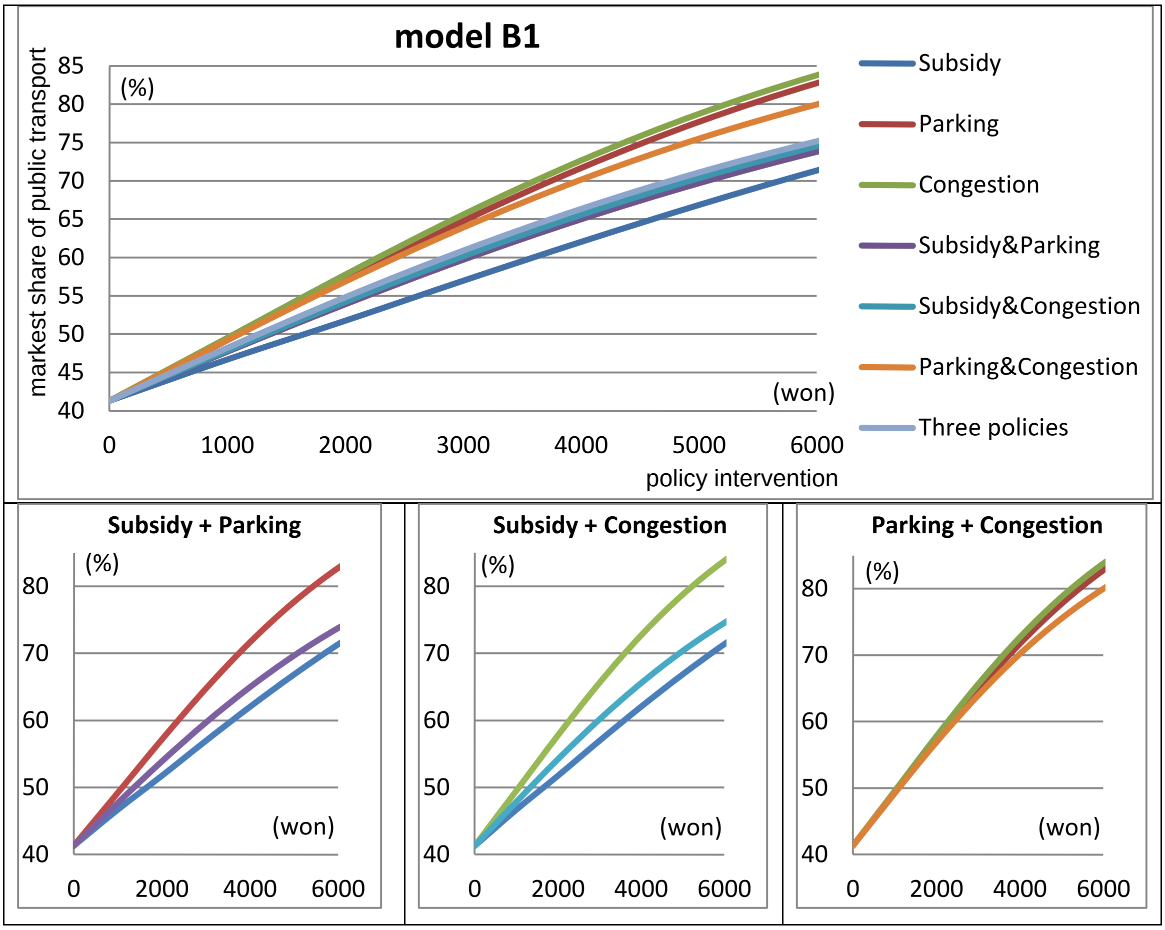
Figure 6-15 compares the market share of PT for two combined MSPs in models 1, which are models with interaction terms including statistically insignificant (i.e. model A1, B1, and C1), at the same monetary level of policy intervention. As shown in **Figure 6-15**, the market share value of PT of the combined MSPs is not settled as intermediate values between the individual MSPs. That is, since there are interaction effects, the market share of PT depends on the sign and the magnitude of coefficients. As shown in **Table 6-13** and **Figure 6-15**, since the signs of the coefficients are positive, interaction effects enhance the utility of car use. That is, the interaction effects reduce the modal shift effects from car to PT. In **Figure 6-15**, the strong influence of interaction makes the slope of the combined MSPs curves go downward steeply. The higher the value of coefficients related to interaction effect, the greater the degree of deviation from approximate average values between the individual MSPs. The modal shift probability curves of the two combined MSPs go downward due to the positive signs of the coefficients.

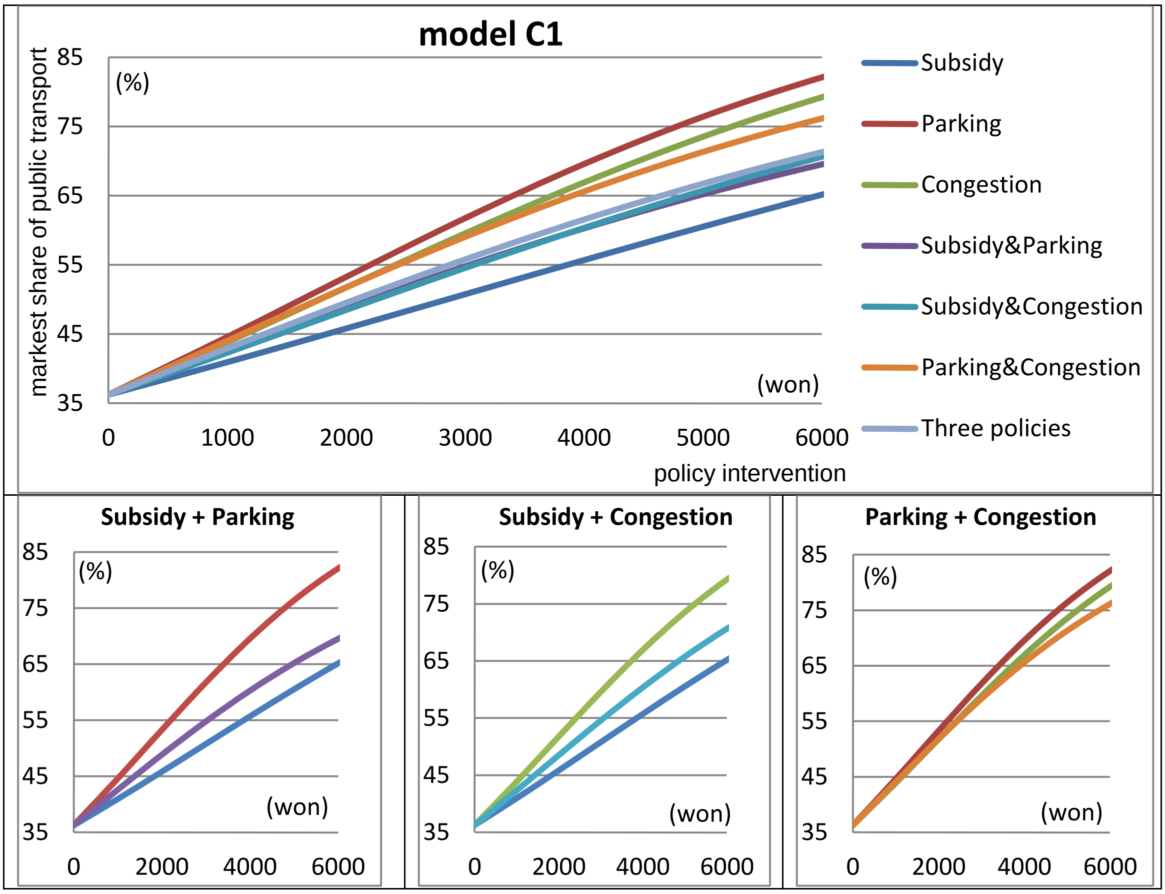
Table 6-13. Values of coefficients in models 1

Classification	Model A1	Model B1	Model C1
β_{12}: subsidy & parking	0.179	0.023	0.028
β_{13}: subsidy & congestion	0.206	0.023	0.015
β_{23}: parking & congestion	**0.242**	**0.025**	**0.039**

Figure 6-15. The market share of PT of the combined MSPs in models 1 at the same monetary level of policy intervention




model B1
markest share of public transport
(%)
85
80
75
70
65
60
55
50
45
40
(won)
0
1000
2000
3000
4000
5000
6000
policy intervention
Subsidy
Parking
Congestion
Subsidy&Parking
Subsidy&Congestion
Parking&Congestion
Three policies
Subsidy + Parking
Subsidy + Congestion
Parking + Congestion
(%)
80
70
60
50
40
(won)
0
2000
4000
6000


model C1
markest share of public transport
(%)
85
75
65
55
45
35
(won)
0
1000
2000
3000
4000
5000
6000
policy intervention
Subsidy
Parking
Congestion
Subsidy&Parking
Subsidy&Congestion
Parking&Congestion
Three policies
Subsidy + Parking
Subsidy + Congestion
Parking + Congestion
(%)
85
75
65
55
45
35
(won)
0
2000
4000
6000

6.5.3. Review of interactions in models 2

Figure 6-16 compares the market share of PT for the combined MSPs in models 2, which are models with interaction terms comprising only statistically significant coefficients, at the same monetary level of policy intervention. As shown in **Table 6-14** and **Figure 6-16**, since the coefficients β_{12} and β_{13} in model C2 do not have any values, the market share value of PT for combined MSPs is settled as intermediate values between the individual MSPs. That is, since there are no interaction effects, the market share value of PT is placed on an approximate average value between the individual MSPs.

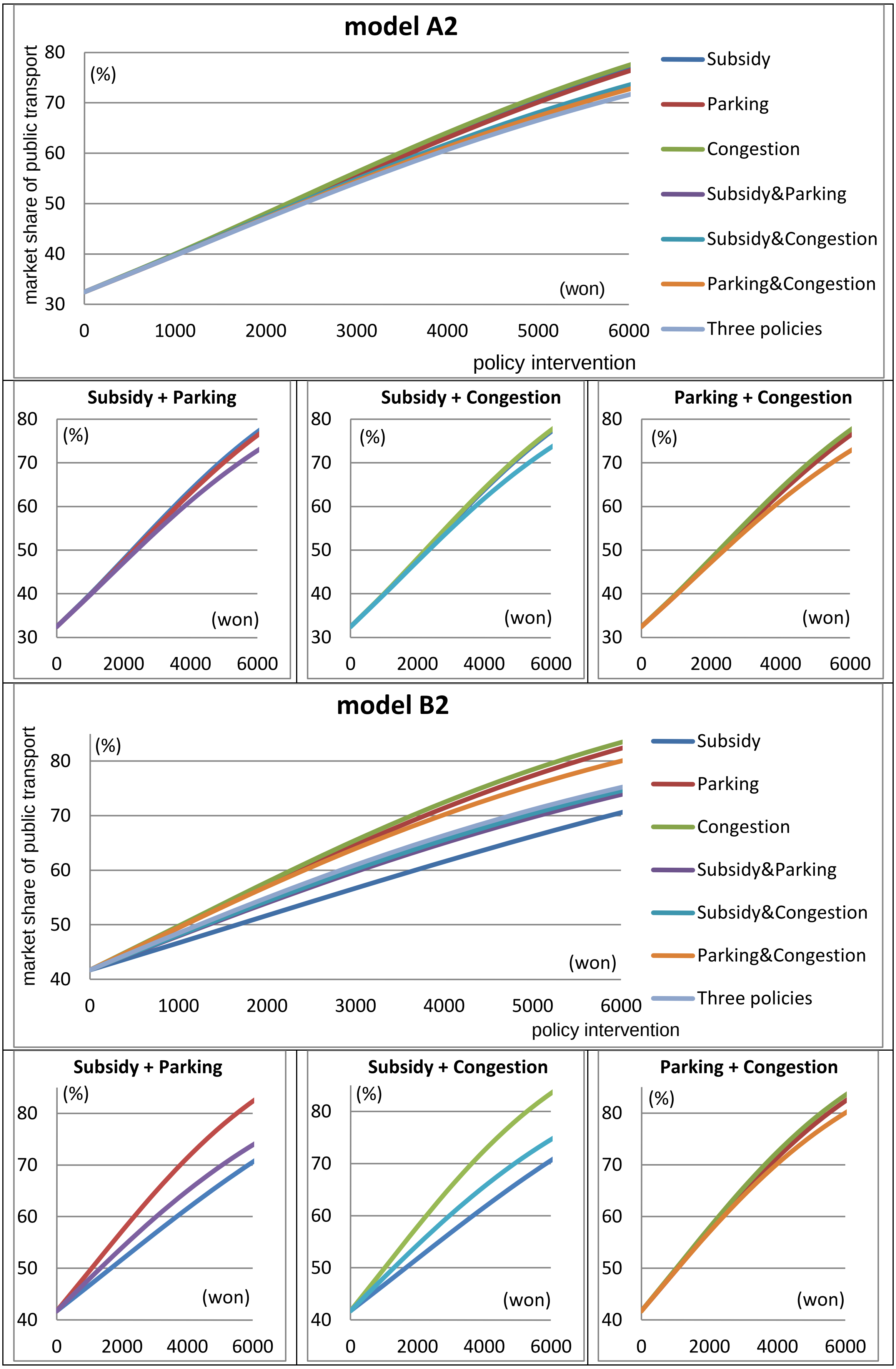
However, if the coefficient has a real value, the market share value of PT for the combined MSPs is determined according to the sign and the magnitude of the coefficients. As shown in **Table 6-14**, since the coefficient β_{23} has a real value (0.030) in model C2, the market share value of PT for the combined MSPs is not determined as an approximate average value between the individual MSPs. In addition, since the sign of the coefficient (β_{23}) is positive, the interaction effect contributes to the increase of car use. In **Figure 6-16**, model C2 shows that the graph of the combination of the additional parking fees and congestion charges is the below graph deviated from approximate average values between the individual MSPs (see the orange coloured graph in model C2). The below graph shows that the combination of the two MSPs makes lower market share value of PT than each MSP. These deviation values detached from the average values may be the negative modal shift synergy effect.

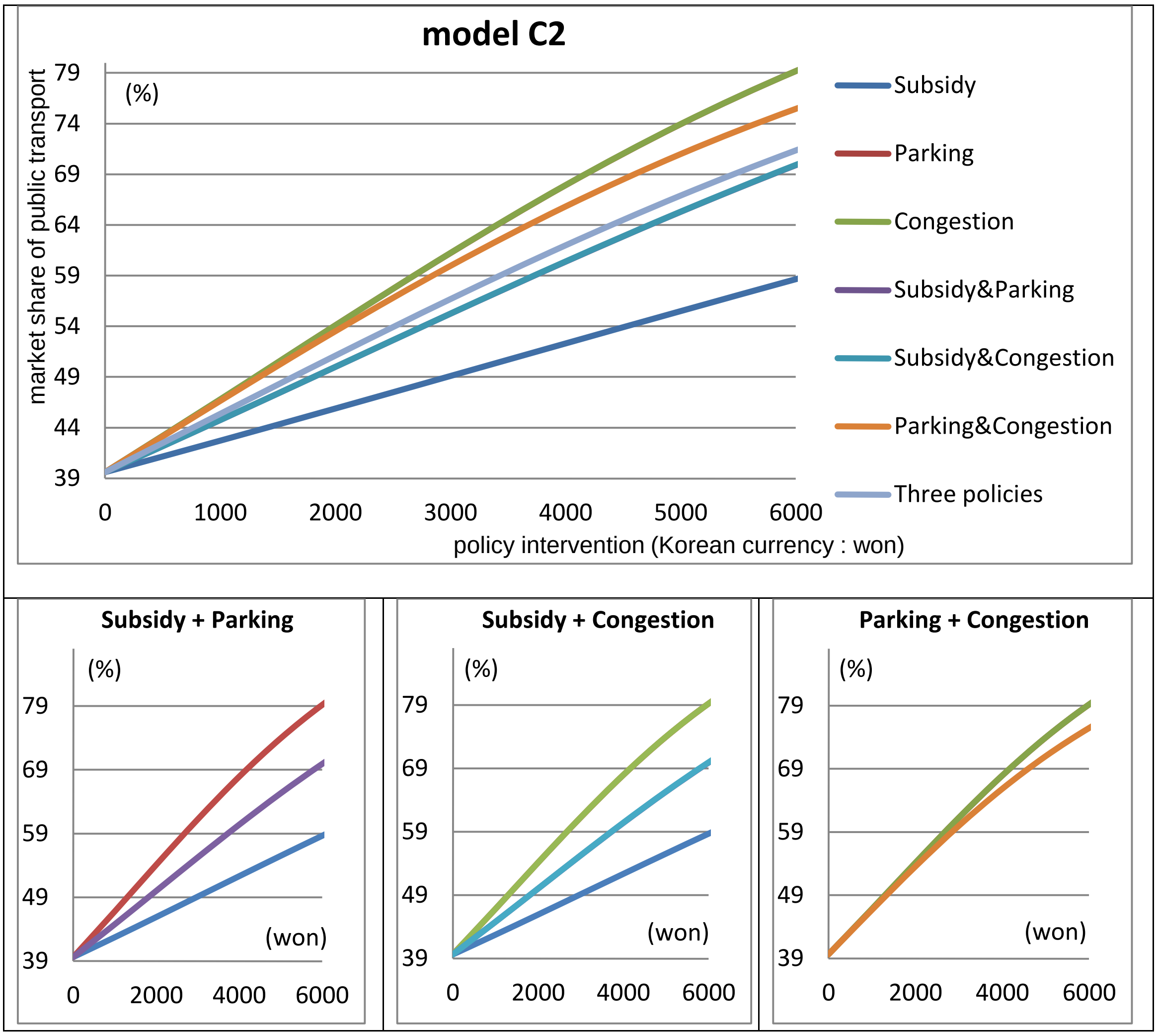
Table 6-14. Value of coefficients in models 2

Classification	Model A2	Model B2	Model C2
β_{12}: subsidy & parking	0.127	0.019	-
β_{13}: subsidy & congestion	0.149	0.019	-
β_{23}: parking & congestion	0.185	0.021	**0.030**

In conclusion, in **Figure 6-16**, the influence of interaction effect makes the slope of curves related to the combined MSPs go downward. This result clearly shows that the two-factor interactions have the negative modal shift effect. In addition, as shown in **Table 6-14** and **Figure 6-16**, the market share value of PT depends on the sign and the magnitude of various coefficients in the utility function. The stronger the interaction of the combined MSPs, the greater the degree of downward deviation from the average values between the individual MSPs. This result indicates that the simultaneous implementation of economic policy intervention can cause the negative modal shift effects in this research.

Figure 6-16. The market share of PT of the combined MSPs in models 2 at the same monetary level of policy intervention





* Parking + Congestion: Since parking curve is almost overlapping with congestion curve, parking curve cannot be seen in the graph.

6.6. Summary

This chapter focuses on the interaction effects between the MSPs. Since in terms of the ρ^2 the models with interaction terms are higher than the models without interaction terms, it is valid to develop models with interaction terms. Meanwhile, the interaction effects of all the three combinations of the two combined MSPs are compared in order to investigate the validity of interaction effect research.

Firstly, the tracking path curves of each model with regard to the change of market share of PT are compared in accordance with the change of allocation ratio of two combined MSPs (e.g. subsidy 0% : parking 100% → 10% : 90% → 20% : 80%). If there are strong interaction effects between the MSPs, the modal shift probability curve shows a curve-shaped line. In contrast, if there are no interaction effects between them, the modal shift probability curve shows a straight line.

Second, through the two methods, modal shift synergy effects are calculated. As a result of the calculation, the modal shift synergy effects of all the combined MSPs show negative results. The highest level of negative modal shift synergy effects would be created by the combination of the additional parking fees and congestion charges whereas the lowest level of negative modal shift synergy effects would be gained by the bond of PT commuting cost subsidies and the congestion charges. The negative synergy effect may stem from the redundancy effect that seems to occur when there are similar characteristics between policies.

Lastly, the market shares of PT of the combined MSPs are compared. If there are no interaction effects between the MSPs, the market share of PT seems to be determined as the average value of each MSP. In contrast, if there are interaction effects between them, these values may depend on the sign and the magnitude of various coefficients in the utility function. In this case, the higher the modal shift effects of the MSPs, the greater the degree of downward deviation from the average values between the individual MSPs.

Chapter 7. Applying the Models to Different Market Segments

7.1. Introduction

The purpose of this chapter is to understand the modal shift effect of the MSP according to various groups and to analyse characteristics of segmented groups. This chapter consists of five further sections. Section 7.2 introduces the segmentation approach, the definition of segmentation and representative types of segmentation research. Section 7.3 considers two types of segmentation approach. Section 7.4 selects a default model B2. Section 7.5 illustrates segmentation with socio-demographic variables. This section includes the size of segments and the correlation of variables. Section 7.6 deals with segmentation based on the attitudinal variables.

7.2. Consideration of Segmentation Analysis

7.2.1. Introduction of segmentation approach

Although making decision related to the choice of travel mode is ultimately based on the mode preference of individuals, exact predictions across various groups can provide better insight and deep understanding of the impact of transport policy (Golias and Yannis, 1998). McFadden (1975) suggested the way of obtaining consistent, unbiased estimates for both aggregate and disaggregate models that consider nonhomogeneous segments and data limitations. McFadden (1975) also demonstrated that "aggregate and disaggregate models have a common foundation and that it may be possible to use a synthesis of the models to facilitate calibration and improve forecasting accuracy". Therefore, McFadden indicated that in order to reduce the errors of aggregate predictions and to improve the prediction of models a segmentation method can be utilized (McFadden and Reid, 1975; McFadden, 1975; Hensher, 1976). A segmentation approach may allow the researcher to fully understand the sensitivity to level of the MSP across segmented groups, to predict more accurate predictions about the behaviour of segmented groups, and to analyse the intrinsic mode preference of segmented groups. That is, separate individual choice models for various groups can allow us to compare the choice of travel mode across segments. According to Bhat (1997), the endogenous market segmentation approach can accommodate systematic heterogeneity and predict a mode choice model for each group.

7.2.2. Definition of segmentation

In discrete choice models, the total number of aggregate outcomes can be divided into different types of individuals. That is, if the researcher has data on the appropriate number of data in each segment, the aggregate outcome variables can be estimated by calculating the choice probability for each segment (Train, 2003). Segmentation can be generally defined as the process of dividing the whole group into different separate groups of individuals sharing the same or similar needs, characteristics or behaviours with the purpose of creating different criteria to meet their specific needs (Lamb et al., 2003; Goyat, 2011). The basic assumption of segmentation is that behavioural responses in each segment should respond differently to variations compared with those in other segments. The whole group can be divided into several groups whose characteristics are relatively homogeneous within a segment and heterogeneous between segments (Kara and Kaynak, 1997).

Segmentation is just a means of achieving the objectives (Fuller et al., 2005). Therefore, the accurate and concrete objectives for segmenting are important to achieve effective results of segmentation. General reasons to the segment are usually practical. In general, segmentation analysis tends to involve understanding of a particular market, enhancement of the ability to identify and exploit opportunities, improvement of the prediction of customer's behaviour, selection of target audiences, and the development of appropriate strategies (Fuller et al., 2005).

Simple segmentation is so common in the analysis of transport policy that it is often not formally labelled as segmentation. Where segmentation is not related to substantial main research or is on the fringe of research, we can label it a 'segmentation exercise' rather than 'segmentation research' (Sullivan and O'Fallon, 2009). Segmentation exercises using the way of dividing target markets should be encouraged as easier, simpler or cheaper methods since it can give new insights and a deeper understanding of the characteristics of the target audiences.

7.2.3. Type of segmentation in the transport sector

Deciding how best to do market segmentation is often not easy because there are many ways of segmentation and the diversity of these ways. Furthermore, no one segmentation method is the best research. The methods of segmentation vary in the perspective of the process of segmentation, the basis of segments, and the type of data. **Table 7-1** shows different methods of segmentation (Sullivan and O'Fallon 2009).

Table 7-1. Different methods of doing segmentation

Classification	Content
Process of Segmentation	· Pre-determined segmentation · Market-defined segmentation * Whether the number of segments and how people are to be split between them is known in advance of data collection or only after collection of market data
Basis of segmentation	· Geographic segment: region, size of city, density of population · Demographic segment: age, gender, household size, number of households · Socio-economic segment: education, occupation, income · Behavioural segment: frequency of car usage · Psychographic segment: attitudes, values, perceptions, opinions · Benefits segment: perceived costs and benefits
Type of data	· Quantitative data (e.g. from surveys) · Qualitative data (e.g. from focus groups)

* Source: Sullivan and O'Fallon, 2009.

Pre-determined segmentation ('a priori segmentation') is a procedure of splitting up the whole group by an accepted classification procedure related to variations (Neal, 2005). This segmentation is based on the notion that there are acceptable stereotypes of variables or known characteristics about different groups. In general, to achieve effective results of segmentation, appropriate selection of segments that are measurable, substantial, accessible and actionable is required (Kotler et al., 2001).

Market-defined segmentation ('post hoc segmentation') does not start with a firm judgment that a factor will determine the segments (Sullivan and O'Fallon 2009). Instead, statistical techniques of exploring groupings are used to analyse data collected on some variables. This segmentation is based on the results of the survey. The segments are not determined until the data are collected (Matear, 1991). That is, the segments are created by multivariate statistical analysis. In general, factor analysis followed by cluster analysis is used commonly. In most cases, the grouping is the result of a cluster analysis (Haustein and Hunecke, 2013). Through a post hoc segmentation analysis, the researcher can gain a better understanding of the target audience from the originally undefined characteristics. In recent years, multidimensional segmentation, artificial neural networks, latent class models, fuzzy and overlapping clustering, and occasion base segmentation have been developed (Neal, 2005). This approach usually used to be utilized in the private marketing sectors.

Although segments can be classified as a geographic, demographic, socio-economic, behavioural and psychographic basis, two or more of segments are often used in reality. Segments tend to provide important information about individuals within specific fields. In general, most of the research related to segmentation technique is prone to use quantitative data since it is difficult to find qualitative segmentations.

7.3. Two types of Segmentation Approaches

7.3.1. Review of two segmentation approaches

Two types of representative segmentation approach can be used in the application of a discrete choice. That is, segmentation methods used as usual can be divided into two methods: a segmentation method using dummy variables and a segmentation method using separate data for segmented groups.

First, one possible way of analysing the modal shift effects of MSPs for different segments is to develop separate models for each category. In this method, the first step is to split the data set into categorical segments. After that, separate coefficient estimates of MSPs for each segmented category or each explanatory variable can be created. This method is the widely used, simple, and straightforward method of stratification of the model (Wardman, 1988). However, there is a drawback of this method. That is, the small number of samples for each segment is prone to increase the standard errors of the estimates (Wardman, 1988). However, segmentation method using separate data for segmented groups can be used to more accurately predict the sensitivity to the level of MSPs across segmented groups.

Second, according to Wardman (1988), dummy variables can be specified to allow pertinent coefficients to differ across segments. If the response to fluctuations in variable X_1 is assumed to be affected by a particular explanatory variable, the segmentation of variables X_1 in the model would be specified as follows (Wardman, 1988):

$$Dummy_{1i} \cdot \Delta X_{1i} + Dummy_{2i} \cdot \Delta X_{1i} + \cdots + Dummy_{ni} \cdot \Delta X_{1i}$$

where if an individual *i* belongs to the *n*-th category of the explanatory variable, $Dummy_{ni}$ will be one, and otherwise zero. And, ΔX_{1i} stands for the difference in variable X_1 between travel modes for individual *i*. This approach can be applied into more general segmentation procedure. That is, other explanatory variables can be segmented and the same variables can be segmented by other explanatory variables such as attitudinal variables and socio-economic variables (Wardman, 1988). In conclusion, segmentation method using dummy variables can be used in order to understand the pattern of mode preference across segmented groups (Bhat, 1997)

7.3.2. Strength and weakness of two segmentation approaches

Segmentation method using dummy variables has two main benefits compared to segmentation method using separate data for segmented groups. First, this segmentation method early can compare the ρ^2 of a basic model (a default model) with that of a segmented model having two or three dummy variables. For examples, if the ρ^2 of a segmented model is higher than a default model, it would be accepted that the validity of the segmented model increases. That is, the segmented model which has higher ρ^2 than the default model can be regarded as a better model. Second, through this segmentation method, the relative differences of transport behaviour between segmented groups at the present state can be compared. That is, through the estimation of a model holding the same ASC and the same coefficients of MSP variables regardless of segmented groups, the relative mode preferences of categorical groups can be more accurately compared. Due to these same ASC and coefficients, the influence of dummy variables for each segment can be measured more exactly. However, through this segmentation method, the intrinsic mode preferences of each categorical group and inherent sensitivity to level of MSPs for each categorical group cannot be fully comprehended. This is mainly because the coefficients of each MSP variable in the segmentation model using dummy variables are fixed values.

Conversely, a segmentation method using a separate data for segmented groups also has distinct advantages compared to the segmentation method using dummy variables. Due to the estimation of using independent and separate data of particular categorical groups, this segmentation method can represent different sensitivity to the level of the MSPs to each segmented groups. The values of the coefficients of the MSPs for each segment and the values of the ASC for each segment are respectively different from those of other segments. Due to the different ASC and different coefficient of the MSP for each segment, the intrinsic sensitivity to the level of each MSP for each segment can be obtained. That is, through the segmentation method using separate data for segmented groups, the modal shift effects of each MSP for each categorical group and the intrinsic mode preferences of each categorical group can be understood better than ones obtained from the segmentation method using dummy variables. However, without unified criteria, this segmentation method cannot grasp exactly the relative mode preferences of each categorical group (e.g. intercept of each segmented group). In addition, since this segmentation method requires too many models, the process of model estimation is complicated and time-consuming.

Since each segmentation method has the strength and weakness in itself, the segmentation method depends on the purpose of the research and the research objective in general. The main purpose of this research is to accurately understand the modal shift effects of MSPs for each segment. However, the better insight into factors affecting travel mode choice *i* is an important issue in this research.

Thus, the understanding of the differences in each segment can be a main objective of the research. Therefore, two segmentation methods run parallel to fully understand the sensitivity to the level of MSPs for each segment and get an insight of main factors influencing the commuter behaviour.

7.4. Selection of a Default Model

This segmentation analysis chooses model B0 as a default model. That is, model B0, which comprises the main MSP coefficients without interaction terms, is selected as the default model (since the results of segmentation analysis in model B2 are almost the same as those of model B0, this research focuses on the segmentation analysis of model B0. The results of segmentation analysis of model B2 can be seen in **Reference Data 1** (**page 372**) and **Reference Data 2** (**page 409**)). In the segmentation analysis, many coefficient estimates associated with interaction terms are expected to be statistically insignificant. In addition, the segmentation analysis for models holding too many coefficients does not always provide significant results. That is, complicated analysis and excessive burdens can be prevented by using model B0. Furthermore, among models without interaction terms, the ρ^2 of model B0 (0.324) is higher than that of model A0 (0.282) and model C0 (0.278). Therefore, in this research, model B0 will be segmented by various segmenting variables. The utility function of model B0 is as follows:

$$V_{car} = \beta_0 + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j \tag{7-1}$$

$$V_{PT} = \beta_1 \cdot Subsidy_j \tag{7-2}$$

Table 7-2. The coefficients of model B0

Coefficient	Beta	Value	Se	t-value	P	Goodness of fit of the statistics
Alternative-Specific Constant (ASC)	β_0	0.334	0.050	6.669	0.000	L(0) = - 12405.3
PT commuting cost subsidy	β_1	0.202	0.016	12.660	0.000	$L(\widehat{\beta})$= - 8354.57
Additional parking fee	β_2	-0.312	0.016	-19.586	0.000	ρ^2= 0.324
Congestion charge	β_3	-0.325	0.014	-23.393	0.000	Number of observations : 678

Table 7-2 shows the coefficients of model B0. To keep the standard errors for a model acceptably small, the segmentation models used to be limited to one segment variable per model, with a maximum of only three categories (Wardman, 1988). Therefore, these analyses are limited to one segment variable per model, with a maximum of three categories.

7.5. Segmentation with Socio-demographic Variables

7.5.1. Socio-demographic variables and size of segments

The researcher has undertaken SP experiments to explore the sensitivity to the level of three MSPs under the hypothetical MSPs. In this research, segmentation analyses are needed to make more accurate predictions or forecasts for each sub-market independently, and to get an insight of the difference of mode preferences between sub-markets.

The object of this research is to understand the mode preferences of main segmented groups and to predict the conversion effect of MSP. To easily achieve the aim, a binary logit model that includes the attributes of the stated choice experiments is selected as a default model. In this study, segments are based on demographic variables and socio-economic variables. Deciding segments is one of the main issues in estimating separate individual choice models (Golias and Yannis, 1998). The segmentation approach, which distinguishes among different choice-set groups, should address the problem of inadequate or unrealistic distinction. Most segmenting variables are categorical data whereas some segmenting variables are continuous data. However, continuous data are converted into categorical data to build segmentation methods. In addition, **Table 7-3** shows main segmentation variables with the corresponding sample sizes for each sub-group. In general, the size of segments should be considered to reduce the error. Due to this reason, the minimum size of each segment is more than 100 samples in the research.

Table 7-3. Segmenting variables and sample size

Variable	Segment	Number	Percent	Valid percent
Region (home places)	In Seoul	466	60.8	61.2
	Outside of Seoul	296	38.6	38.8
	Total	762	99.4	100
	Missing	5	0.6	
Gender	Male	647	84.4	85.1
	Female	113	14.7	14.9
	Total	760	99.1	100
	Missing	7	0.9	
Age	20-30s	283	36.9	37.3
	40s	346	45.1	45.6
	50s+	130	17.0	17.1
	Total	759	99	100
	Missing	8	1	
Education	Below university	47	6.1	6.2
	Undergraduate	493	64.3	64.7
	Postgraduate	222	28.9	29.1
	Total	762	99.3	100
	Missing	5	0.7	

Work	Administrative or clerical sector	319	41.6	41.8
	Other	444	57.9	58.2
	Total	763	99.5	100
	Missing	4	0.5	
Income	Up to 5,000,000 won	343	44.7	44.9
	5,000,001~7,000,000 won	225	29.3	29.5
	More than 7,000,001 won	196	22.6	25.6
	Total	764	99.6	100
	Missing	3	0.4	
Child	Having a child or children	377	49.2	49.6
	Not having a child	383	49.9	50.4
	Total	760	99.1	100
	Missing	7	0.9	
Distance	Less than 10km	194	25.3	27.1
	10.1km ~ 20km	278	36.2	38.9
	More than 20km	243	31.7	34.0
	Total	715	93.2	100
	Missing	52	6.8	
Car number	1	529	69.0	69.5
	2 or more	232	30.2	30.5
	Total	761	99.2	100
	Missing	6	0.8	
Car commuting time	Up to 40 minutes	318	41.4	47.7
	More than 41 minutes	348	45.4	52.3
	Total	666	86.8	100
	Missing	101	13.2	
Main commute mode	car user as a driver or passenger	312	40.7	40.7
	Other	454	59.2	59.3
	Total	766	99.9	100
	Missing	1	0.1	
Main use of respondent's car	Commute to/from work or school	360	46.9	48.5
	Other	382	49.8	51.5
	Total	742	96.7	100
	Missing	25	3.3	
Total		767	100	

7.5.2. Correlation of socio-demographic variables

Table 7-4 shows the correlation of segmented variables. In general, Pearson correlation[11] coefficients can be defined as the covariance of the variables divided by the product of standard deviations. The signs of correlation coefficients represent the direction of the relationship between the two variables.

[11] The correlation between variables is a measure of how well the variables are related. The most common measure of correlation in statistics is the Pearson Correlation, which shows the linear relationship between two variables (Kinnear and Gray, 1999; Rumsey, 2007). Results are between −1 and 1 ($-1 \le r \le +1$). While a result of −1 means that there is a perfect negative correlation between the two variables, a result of 1 means that there is a perfect positive correlation between the two variables (Kinnear and Gray, 1999). The closer the value of r gets to zero, the greater the variation the data points are around the line of best fit. While positive correlation means that the other variable has a tendency to increase, negative correlation means that the other variable has a tendency to decrease. In general, while more than 0.4 value of r means that significant correlation in terms of statistics exists, more than 0.7 value of r means that high correlation exists.

The positive sign of correlation means an affirmative relationship between the two variables whereas the negative one implies a reverse relationship between them. For example, in the case of a positive correlation, if the value of one variable increases, the value of the other variable will increase. In addition, the magnitude of correlation coefficients represents the strength of the relationship between two variables. If two variables have a strong correlation, the absolute magnitude of correlation coefficients will be close to one.

Table 7-4. Correlation analysis of segmented variables

Classification		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Correlation	1	-0.073*	0.074*	-0.118**	-0.045	-0.059	0.057	**0.594****	0.121**	**0.286****	-0.010	-0.029
	Sig. (2-tailed)		0.044	0.042	0.001	0.218	0.104	0.118	0.000	0.001	0.000	0.784	0.440
	N		755	754	757	758	759	755	711	756	662	761	737
(2)	Correlation		1	-0.137**	0.014	0.022	0.018	-0.115**	-0.097**	0.051	-0.030	0.006	-0.052
	Sig. (2-tailed)			0.000	0.707	0.550	0.618	0.001	0.010	0.162	0.449	0.877	0.155
	N			756	757	758	759	755	708	754	661	759	735
(3)	Correlation			1	0.079*	-0.111**	**0.360****	0.067	0.100**	0.138**	0.010	**-0.237****	**-0.260****
	Sig. (2-tailed)				0.030	0.002	0.000	0.067	0.008	0.000	0.791	0.000	0.000
	N				756	757	758	754	707	753	659	758	734
(4)	Correlation				1	-0.114**	0.180**	0.032	-0.096*	0.082*	-0.110**	-0.085*	-0.098**
	Sig. (2-tailed)					0.002	0.000	0.384	0.011	0.024	0.005	0.019	0.008
	N					760	761	757	711	756	662	761	738
(5)	Correlation					1	-0.031	-0.055	-0.027	-0.163**	-0.038	0.129**	0.019
	Sig. (2-tailed)						0.387	0.132	0.477	0.000	0.325	0.000	0.608
	N						762	758	711	757	663	762	738
(6)	Correlation						1	0.127**	-0.094*	**0.206****	-0.082*	-0.173**	-0.129**
	Sig. (2-tailed)							0.000	0.012	0.000	0.035	0.000	0.000
	N							759	712	758	664	763	739
(7)	Correlation							1	0.037	0.022	0.016	-0.054	-0.007
	Sig. (2-tailed)								0.330	0.547	0.683	0.139	0.853
	N								709	754	661	759	735
(8)	Correlation								1	0.090*	**0.492****	0.040	-0.001
	Sig. (2-tailed)									0.017	0.000	0.291	0.986
	N									709	621	715	692
(9)	Correlation									1	0.044	-0.199**	-0.137**
	Sig. (2-tailed)										0.254	0.000	0.000
	N										663	760	740
(10)	Correlation										1	0.054	0.085*
	Sig. (2-tailed)											0.163	0.029
	N											666	657
(11)	Correlation											1	**0.554****
	Sig. (2-tailed)												0.000
	N												741
(12)	Correlation												1
	Sig. (2-tailed)												
	N												

* (1) Region (home places), (2) Gender, (3) Age, (4) Education, (5) Work, (6) Income, (7) Child, (8) Distance, (9) Car number, (10) Car commuting time, (11) Main commute mode, (12) Main use of respondent's car
* Superscript ** : Correlation is significant at the 0.01 level (2-tailed).
* Superscript * : Correlation is significant at the 0.05 level (2-tailed).

In **Table 7-4**, the value of Pearson correlation between 'the region variable' and 'the distance from home to work variable' is 0.594. Since the sign of the correlation is positive, it can be concluded that the relationship between them is medium positive. This correlation is significant at the 99% level of confidence since the value of significance is 0.000. In general, the value of significance means the statistical probability of getting a result that is as extreme as one which was observed. Meanwhile, the value of Pearson correlation between 'the distance from home to work' and 'the commuting time of car use' is 0.492, while the one between 'the type of main travel mode' and 'the main purpose of car usage' is 0.554. These relationships also seem to be medium positive. However, since the values of correlation for the rest of the segmented variables, except for the previous three correlations, are less than 0.4, it can be concluded that the correlations of the rest of the segmented variables are very weak.

7.5.3. Result of segmentation with socio-demographic variables (Region)

In general, the regional factor is used to be the main segmentation analysis in the transportation research. In this research, the regional factor can be classified into two categories: people who live in Seoul and those who live outside of Seoul. The basic assumption is that people who live in Seoul might behave differently from people who live outside of Seoul.

7.5.3.1. Application of the segmentation method using dummy variables

In **Table 7-5**, the ρ^2 of the segmented model (0.329) is higher than that of the default model (0.324). Therefore, it can be inferred that the validity of the segmented model increases rather than the default model (model B0). In addition, the signs and the orders of the absolute magnitude of the coefficients for MSP in the segmented model are the same as those of the default model (model B0). That is, congestion charges (β_3: $-$ 0.2466) have the highest value, with additional parking fees (β_2: $-$ 0.2289) the next highest value, and the lowest value generated by PT commuting cost subsidies (β_1: 0.1249).

Table 7-5. The coefficients of a segmented model with a dummy variable (Region)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**0.0333**	0.8153
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1249**	**13.4701****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2289**	**-23.4026****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2466**	**-29.5376****
Dummy region (in Seoul: 0, **outside of Seoul: 1**)	β_{region}			**0.1297**	**3.2474****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8327.889	
ρ^2		0.324		0.329	
Number of observations		678		674	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

As indicated in **Table 7-5**, regardless of whether a respondent corresponds to a dummy variable, the values of ASC (β_0) and the values of the coefficients of MSPs (β_1, β_2 and β_3) are constant. Due to this reason, the influence of the dummy variable (people who live in Seoul:0, people who live outside of Seoul:1) can be clearly represented in **Figure 7-1**.

The deterministic utility term (V_k) function form of model B0 segmented by the regional dummy variable is as follows:

$$V_{car} = \beta_0 + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{region} \cdot Dummy\ Region \text{ (in Seoul:0, outside of Seoul:1)} \quad (7\text{-}3)$$

$$V_{PT} = \beta_1 \cdot Subsidy_j \qquad (7\text{-}4)$$

In the specification of the segmented model, a dummy variable is composed of two components: a coefficient (i.e. β), implying utility weight of the dummy variable, and an attribute (i.e. *Dummy Region*), indicating whether the respondents corresponds to a particular segmented group or not. That is, if a respondent lives outside of Seoul, the value of the dummy attribute (indicator) will be 1. Conversely, if a respondent lives in Seoul, the value of the dummy attribute will be 0. Therefore, it can be interpreted that the influence of default value (people who live in Seoul) includes the value of ASC. Meanwhile, if a respondent lives outside of Seoul, the value of the coefficient (0.1297) is multiplied by the value of the attribute (1) (= 0.1297×1). Thus, the utility value of the dummy variable will be 0.1297. In addition, since the dummy variable belongs to the utility function of car use, positive sign contributes to the increase of the utility of the car. In short, it can be concluded that when there is no policy intervention, people who live outside of Seoul prefer car use.

The utility value of a travel mode can be calculated as follows:

$$V_{car} = 0.0333 + (-0.2289) \cdot Park_j + (-0.2466) \cdot Congestion_j + (0.1297) \cdot Dummy\ Region$$
$$\text{(in Seoul:0, outside of Seoul:1)} \qquad (7\text{-}5)$$

$$V_{PT} = (0.1249) \cdot Subsidy_j \qquad (7\text{-}6)$$

If no policy intervention is supposed, the utility of the respondent who lives outside of Seoul is as follows:

$$V_{car} = 0.0333 + (-0.2289) \cdot (0) + (-0.2466) \cdot (0) + (0.1297) \cdot (1) = 0.163,\ U_{car} = e^{0.163} = 1.177037 \qquad (7\text{-}7)$$

$$V_{PT} = (0.1249) \cdot (0) = 0, \qquad U_{PT} = e^0 = 1 \qquad (7\text{-}8)$$

$$P^i_{car} = \frac{e^{V_{i,car}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{1.177037}{1.177037 + 1} = 0.54066 \cong 54.07\% \qquad (7\text{-}9)$$

$$P^i_{PT} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{1}{1.177037 + 1} = 0.45934 \cong \mathbf{45.93\%} \qquad (7\text{-}10)$$

The modal shift probability (market share of PT) of the respondent who lives outside of Seoul is 45.93%. This percentage implies the intercept of the MSP curves in **Figure 7-1** (see dotted lines).

The utility of the respondent who lives in Seoul can be calculated as follows:

$$V_{car} = 0.0333 + (-0.2289) \cdot (0) + (-0.2466) \cdot (0) + (0.1297) \cdot (0) = 0.0333,$$
$$U_{car} = e^{0.0333} = 1.033861 \qquad (7\text{-}11)$$

$$V_{PT} = (0.1249) \cdot (0) = 0, \qquad U_{PT} = e^0 = 1 \qquad (7\text{-}12)$$

$$P^i_{car} = \frac{e^{V_{i,car}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = 0.508324 \cong 50.83\% \qquad (7\text{-}13)$$

$$P^i_{PT} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{1}{1.033861 + 1} = 0.491676 \cong \mathbf{49.17\%} \qquad (7\text{-}14)$$

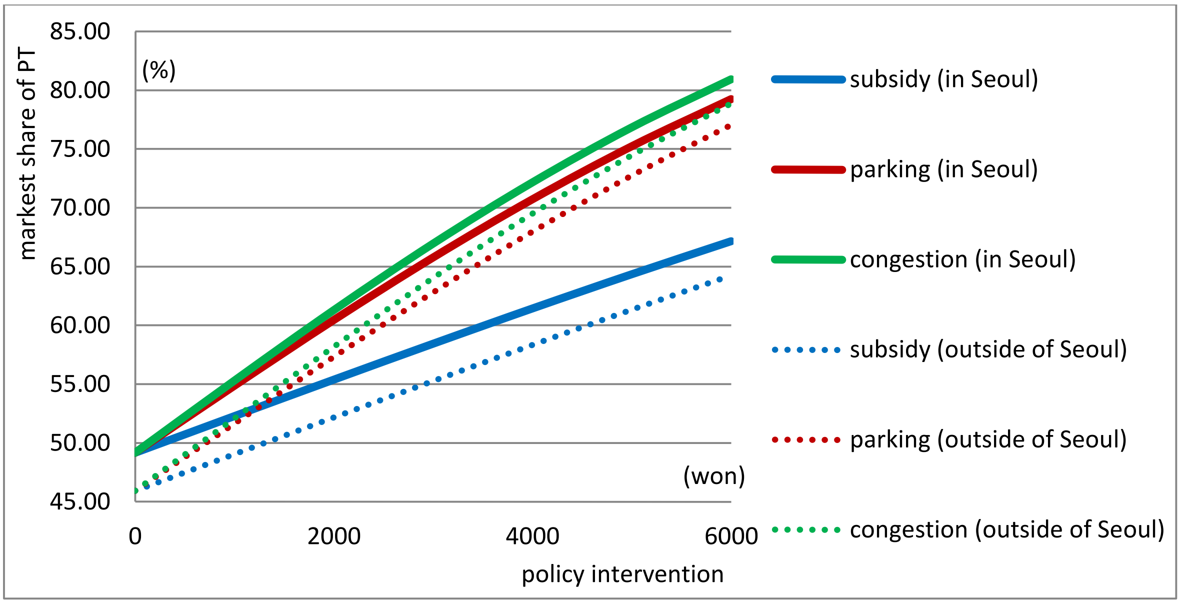
The modal shift probability of the respondent who lives in Seoul is 49.17% (see **Table 7-6)**. This percentage means the intercept of the modal shift probability in **Figure 7-1** (see straight lines).

Table 7-6. The market share of PT in a segmented model using a dummy variable (Region) (unit: %)

Region	MSP	0 won	1,000 won	2,000 won	3,000 won	4,000 won	5,000 won	6,000 won
In Seoul	Subsidy	49.17	52.29 (6.35)	55.39 (12.65)	58.45 (18.87)	61.45 (24.97)	64.36 (30.89)	67.17 (36.61)
	Parking	49.17	54.87 (11.59)	60.46 (22.96)	65.78 (33.78)	70.73 (43.85)	75.24 (53.02)	79.25 (61.18)
	Congestion	49.17	55.31 (12.49)	61.30 (24.67)	66.96 (36.18)	72.17 (46.78)	76.85 (56.29)	**80.94 (64.61)**
Outside of Seoul	Subsidy	45.93	49.05 (6.79)	52.17 (13.59)	55.27 (20.34)	58.34 (27.02)	61.34 (33.55)	64.25 (39.89)
	Parking	45.93	51.65 (12.45)	57.32 (24.80)	62.80 (36.73)	67.97 (47.99)	72.74 (58.37)	77.04 (67.73)
	Congestion	45.93	52.09 (13.41)	58.18 (26.67)	64.03 (39.41)	69.50 (51.32)	74.46 (62.12)	**78.86 (71.70)**

By judging from the position of the intercept for each segmented group, the preference of travel mode for each group without policy intervention can be understood. These intercepts in the vertical axis correspond to the values in **Equation 7-10** and **Equation 7-14**. It seems that the coefficient of the dummy variable (β_{region}) affects the position of the intercept. The segmentation method using the dummy variable provides better understanding of the influence of the dummy variable. However, it seems that the slopes of each MSP of the two segmented groups are almost similar since the coefficient values of MSPs and ASC are the same irrespective of segmented groups.

Figure 7-1. The modal shift probability curves in a segmented model using a dummy variable (Region)



7.5.3.2. *Application of the segmentation method using separate data of the segmented groups*

In the separate models for each segment using separate data, the different marginal utilities of each MSP and different ASC of each model can be seen in **Table 7-7**. This segmentation method is helpful not only for comprehending the intrinsic characteristics of each segment but also for predicting the modal shift effects of MSP in each segment.

However, this segmentation method cannot accurately compare the ρ^2 of a default model B0 with those of the segmented models. As shown in **Table 7-7**, the ρ^2 (0.324) of the default model is lower than that (0.331) of the segmented model with people who live in Seoul, but is higher than that (0.317) of the segmented model with people who live outside of Seoul. Therefore, this method cannot judge whether the segmented model is better than the default model or not.

Table 7-7. The coefficients of the segmented models using separate data (Region)

Coefficient		In Seoul		Outside of Seoul	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.1238**	**2.4521***	0.0707	1.1435
PT commuting cost subsidy	β_1	**0.1809**	**12.0481****	**0.0860**	**7.3634****
Additional parking fee	β_2	**-0.2296**	**-18.1457****	**-0.2289**	**-14.8215****
Congestion charge	β_3	**-0.2481**	**-22.9728****	**-0.2452**	**-18.6024****
L(0)		-7455.491		-4874.904	
L($\widehat{\beta}$)		-4986.948		-3328.299	
ρ^2		0.3311		0.3173	
Number of observations		466		296	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

The deterministic utility term (V_k) function form of segmented models using separate data is as follows:

$$V_{car} = \beta_0 + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j \tag{7-15}$$

$$V_{PT} = \beta_1 \cdot Subsidy_j \tag{7-16}$$

If no policy intervention is supposed, the utility of the respondent who lives outside of Seoul is as follows:

$$V_{car} = 0.0707 + (-0.2289)\cdot(0) + (-0.2452)\cdot(0) = 0.0707, \quad U_{car} = e^{0.0707} = 1.073259 \tag{7-17}$$

$$V_{PT} = (0.0860)\cdot Subsidy_j = (0.0860)\cdot(0) = 0, \quad U_{PT} = e^{0} = 1 \tag{7-18}$$

$$P_{PT}^{i} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{1}{1.073259 + 1} = 0.482332 \cong \mathbf{48.23\%} \tag{7-19}$$

The choice probability of PT use for the respondent who lives outside of Seoul is 48.23% (see **Table 7-8**). This percentage implies the intercept of the modal shift probability curve in **Figure 7-2** (see straight lines).

If no policy intervention is supposed, the utility of the respondent who lives in Seoul can be calculated as follows:

$$V_{car} = 0.1238 + (-0.2296)\cdot(0) + (-0.2481)\cdot(0) = 0.1238, \quad U_{car} = e^{0.1238} = 1.131789 \tag{7-20}$$

$$V_{PT} = (0.1809)\cdot Subsidy_j = (0.1809)\cdot(0) = 0, \quad U_{PT} = e^{0} = 1 \tag{7-21}$$

$$P_{PT}^{i} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{1}{1.131789 + 1} = 0.469089 \cong \mathbf{46.91\%} \tag{7-22}$$

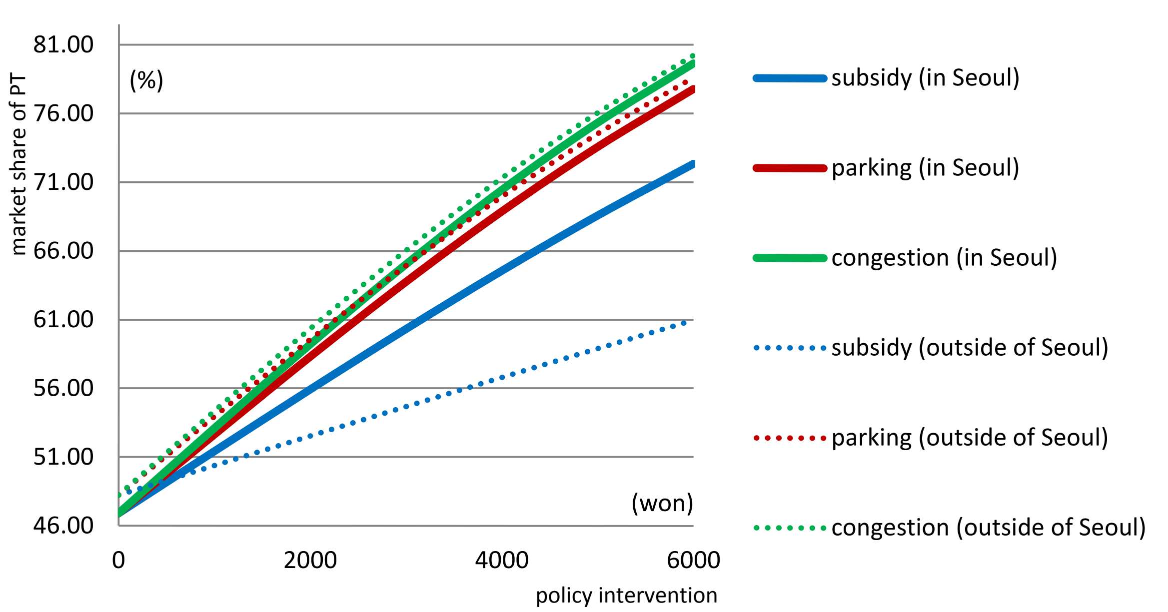
The modal shift probability (market share of PT) for the respondent who lives in Seoul is 46.91%. This percentage means the intercept of the modal shift probability curve in **Figure 7-2** (see dotted lines).

Table 7-8. The market share of PT in segmented models using separate data (Region) (unit: %)

Region	MSP	0 won	1,000 Won	2,000 won	3,000 Won	4,000 Won	5,000 won	6,000 Won
In Seoul	Subsidy	46.91	51.43 (9.63)	55.92 (19.21)	60.32 (28.59)	64.56 (37.63)	68.58 (46.20)	72.34 (54.22)
	Parking	46.91	52.64 (12.22)	58.31 (24.30)	63.76 (35.92)	68.88 (46.84)	73.58 (56.85)	77.80 (65.84)
	Congestion	46.91	53.10 (13.21)	59.20 (26.21)	65.03 (38.64)	70.45 (50.17)	75.34 (60.60)	79.65 (69.81)
Outside of Seoul	Subsidy	48.23	50.38 (4.46)	52.53 (8.91)	54.67 (13.34)	56.79 (17.74)	58.89 (22.09)	60.95 (26.37)
	Parking	48.23	53.95 (11.85)	59.56 (23.48)	64.93 (34.62)	69.95 (45.02)	74.53 (54.52)	78.63 (63.02)
	Congestion	48.23	54.35 (12.68)	60.34 (25.10)	66.04 (36.91)	71.30 (47.83)	76.05 (57.67)	80.23 (66.33)

Figure 7-2 shows that people who live outside of Seoul prefer the use of PT rather than people who live in Seoul since the position of the intercept for people who live outside of Seoul on the vertical axis is a little higher than people who live in Seoul. This result is different from that of using the dummy variable segmentation method. Although **Figure 7-1** shows that people who live in Seoul prefer the use of PT, **Figure 7-2** seems to show the reverse results. In terms of the judgement of the position of the intercept, a segmented model using dummy variables can be better than a segmented model using separated data. That is, to judge the relative characteristics of the segmented group, a segmented model using dummy variables is more suitable for segmentation analysis. In addition, since the position of the intercept in **Figure 7-2** is not clear compared to **Figure 7-1**, this result seems to indicate a drawback of a segmentation model using separate data. However, through this estimation, the modal shift effects of the MSP can be compared.

Figure 7-2. The modal shift probability curves in segmented models using separate data (Region)



Meanwhile, the market share of PT with regard to PT commuting cost subsidies for people who live outside of Seoul are distinctly lower than other MSPs. That is, although the PT commuting cost of people who live outside of Seoul (mean 2,472.64 won, = £ 1.37) is higher than people who live in Seoul (mean 1,628.45 won, = £ 0.90), the modal shift effect (the marginal utility) of PT commuting cost subsidies for people who live outside of Seoul is obviously lower than that of people who live in Seoul. In addition, as shown in **Table 7-9**, although the income level of people who live outside of Seoul are relatively lower than those who live in Seoul, income distribution factor does not seem to significantly affect weak modal shift effect of PT commuting cost subsidies for people who live outside of Seoul. Therefore, if can be inferred that the intrinsic regional factor affects modal shift effect of PT commuting cost subsidies.

Table 7-9. Distribution of income class classified by region

Classification	In Seoul area	Outside of Seoul area
High-income class	128 (27.47%)	67 (22.64%)
Middle-income class	137 (29.40%)	88 (29.73%)
Low-income class	201 (43.13%)	141 (47.63%)
Total	466 (100%)	296 (100%)

Detailed results of segmentation analysis with other socio-demographic variables are attached to **Appendix 7**.

7.6. Segmentation Result with Attitudinal Variables

7.6.1. Attitudinal variables and correlation of segmented variables

In addition to socio-economic variables, attitudinal variables can be analysed by using segmentation methods. In general, the difference of people's perception and attitude may substantially influence the modal shift effects of the MSP and the choice behaviour of travel mode. Since five-point Likert scale information on individual perception and attitude is obtained from the online survey, segmentation analysis across segmented groups can be carried out in order to understand how attitudinal factors affect the modal shift effects of the MSP and the choice of travel mode. **Table 7-10** shows frequency analysis of individual perception and attitude.

Table 7-10. Frequency analysis of individual perception and attitude

Variable (question)		Opinion	Frequency	Percent	Valid percent	Cumulative percent
Q1. Congestion problems are very severe during the morning peak	Valid	Strongly disagree	6	0.8	0.8	0.8
		Disagree	13	1.7	1.7	2.5
		Neutral	58	7.6	7.6	10.1
		Agree	269	35.1	35.3	45.3
		Strongly agree	417	54.4	54.7	100.0
		Total	763	99.5	100.0	
	Missing	No response	4	0.5		
Q2. The use of PT is important in order to reduce global warming and to protect the environment	Valid	Strongly disagree	5	0.7	0.7	0.7
		Disagree	19	2.5	2.5	3.2
		Neutral	90	11.7	11.9	15.1
		Agree	353	46.0	46.8	61.9
		Strongly agree	287	37.4	38.1	100.0
		Total	754	98.3	100.0	
	Missing	No response	13	1.7		
Q3. The use of PT is helpful for respondent's health	Valid	Strongly disagree	19	2.5	2.5	2.5
		Disagree	97	12.6	12.9	15.4
		Neutral	177	23.1	23.5	39.0
		Agree	248	32.3	33.0	71.9
		Strongly agree	211	27.5	28.1	100.0
		Total	752	98.0	100.0	
	Missing	No response	15	2.0		
Q4. The freedom of choosing transport modes should not be restricted by government regulation	Valid	Strongly disagree	17	2.2	2.3	2.3
		Disagree	86	11.2	11.5	13.7
		Neutral	152	19.8	20.2	34.0
		Agree	298	38.9	39.7	73.6
		Strongly agree	198	25.8	26.4	100.0
		Total	751	97.9	100.0	
	Missing	No response	16	2.1		
Q5. Convenience is a very important factor in determining commuting	Valid	Strongly disagree	0	0	0	0
		Disagree	9	1.2	1.2	1.2
		Neutral	70	9.1	9.2	10.4
		Agree	314	40.9	41.2	51.6
		Strongly agree	368	48.0	48.4	100.0
		Total	761	99.2	100.0	
	Missing	No response	6	0.8		

Q6. Time is a very important factor in determining commuting	Valid	Strongly disagree	2	0.3	0.3	0.3
		Disagree	12	1.6	1.6	1.9
		Neutral	56	7.3	7.4	9.3
		Agree	331	43.2	43.8	53.0
		Strongly agree	355	46.3	47.0	100.0
		Total	756	98.6	100.0	
	Missing	No response	11	1.4		
Q7. Cost is a very important factor in determining commuting	Valid	Strongly disagree	3	0.4	0.4	0.4
		Disagree	35	4.6	4.6	5.0
		Neutral	180	23.5	23.8	28.9
		Agree	356	46.4	47.2	76.0
		Strongly agree	181	23.6	24.0	100.0
		Total	755	98.4	100.0	
	Missing	No response	12	1.6		
Total			767	100		

Figure 7-3 shows questionnaires about individual perception and attitude. Five-point Likert scale is used to measure respondent's perception and attitude by asking the extent to which respondents agree or disagree with a particular statement or question. In this case, respondents choose one of the optional responses. Individual responses using Likert scales are usually treated as ordinal data (Bertram, 2006).

Figure 7-3. Questionnaires of individual perception and attitude

About individual perception and attitude:

To what extent do you agree with the following statements? (tick one only)

Q1. Congestion problems are very severe during the morning peak.

① Strongly disagree ② Disagree ③ Neutral ④ Agree ⑤ Strongly agree

Q2. The use of PT is important in order to reduce global warming and to protect the environment.

① Strongly disagree ② Disagree ③ Neutral ④ Agree ⑤ Strongly agree

Q3. The use of PT is helpful for my health.

① Strongly disagree ② Disagree ③ Neutral ④ Agree ⑤ Strongly agree

Q4. The freedom of choosing transport modes should not be restricted by government regulation.

① Strongly disagree ② Disagree ③ Neutral ④ Agree ⑤ Strongly agree

Q5. Convenience is a very important factor in determining commuting.

① Strongly disagree ② Disagree ③ Neutral ④ Agree ⑤ Strongly agree

Q6. Time is a very important factor in determining commuting.

① Strongly disagree ② Disagree ③ Neutral ④ Agree ⑤ Strongly agree

Q7. Cost is a very important factor in determining commuting.

① Strongly disagree ② Disagree ③ Neutral ④ Agree ⑤ Strongly agree

The Likert scale measures the extent to which the respondent disagrees or agrees with the statements. Scale 5 means 'strongly agree', scale 4 implies 'agree', scale 3 represents 'neutral', scale 2 illustrates 'disagree', and scale 1 means 'strongly disagree'. In the survey, respondents answered their affirmative perception and attitude to the statements as follows: congestion problem (median[12]: 5, mode: 5), convenience importance (median: 4, mode: 4), time importance (median: 4, mode: 4), environment protection (median: 4, mode: 4), cost importance (median: 4, mode: 5), freedom of mode choice (median: 4, mode: 5), and the PT use for human health (median: 4, mode: 4).

Table 7-11 shows the correlation of attitudinal variables. The correlation signs between Q1 (congestion problem) and the other variables are negative. It means that there are reverse relationships between them. The sign of the correlation between Q2 (environmental protection) and Q3 (human health) is positive. This affirmative relationship between environmental protection and human health is acceptable. An interesting indication is that the sign of the correlation between Q5 (convenience) and Q6 (time) is positive whereas the sign of the correlation between Q5 (convenience) and Q7 (cost) is negative. It can be comprehended that respondents who recognize the importance of convenience tend to acknowledge the importance of time, but deny the importance of cost. This correlation is understandable. In addition, the sign of the correlation between Q6 (time) and Q7 (cost) is positive.

Table 7-11. Correlation analysis of attitudinal variables

Classification	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Q1	1	- 0.031	- 0 .040	- 0.044	- 0.033	- 0.029	- 0.001
Q2		1	**0.534****	- 0.025	0.035	0.159**	0.190**
Q3			1	0.016	0.019	0.113**	0.136**
Q4				1	0.161**	- 0.006	0.002
Q5					1	0.082*	- 0.040
Q6						1	0.171**
Q7							1

* Superscript ** : Correlation is significant at the 0.01 level (2-tailed).
* Superscript * : Correlation is significant at the 0.05 level (2-tailed).

The value of the Pearson Correlation (r) between Q1 (congestion problem) and Q2 (environmental protection) is − 0.031. Therefore, since the absolute value of the correlation is less than 0.4, it can be interpreted that the relationship between them is not statistically significant. Most values of correlation between other attitudinal variables are placed between − 0.05 and 0.19. However, notable

[12] For ordinal data which are descriptive codes without numerical value, both the median and the mode can be used. In particular, the median is the most suitable measure for ordinal data. On the other hand, the mode is the only meausre for nominal data (Aristodemou, 2014). Median is the value which occupies the middle position when all the observations are arranged in an increasing or decreasing order whereas mode is the most frequent occurring value in a set of nominal data (Onunwor, 2014; Sundar and Richard, 2012).

is the fact that the value of correlation between Q2 (environmental protection) and Q3 (human health) is 0.534. It indicates a medium positive relationship between them. However, the respective research on Q2 and Q3 can have significant meanings even though the correlation between them is statistically significant. Therefore, the independent research on Q2 and Q3 will be continued. Overall, since the correlations between independent variables are low, it can be regarded that independence of attitudinal variables is satisfied.

7.6.2. Prior review on applying segmentation methods into attitudinal variables

Considering the number of samples, all the attitudinal variables can be divided into three categories: 'strongly agree' (strong positive group), 'agree' (moderate positive group), and 'neutral and others' (negative group). Since many respondent's answers seem to have a tendency of affirmative biases and consideration on sample size is required, three Likert scale groups such as neutral, disagree, strongly disagree can be integrated into one 'neutral and others' segmented group in order to appropriately conduct segmentation research. In the segmentation models considering attitudinal factors, all the coefficients (β_1, β_2 and β_3) of MSP are statistically significant at the 99% confidence interval since the absolute t-values are larger than 2.57.

In this research, segmented groups of people who agree strongly with the statement about attitudinal consciousness are set up as default groups of dummy attributes. Thus, if a respondent agrees strongly with corresponding statements, the utility value of the dummy variable will be zero. Therefore, since the default value of dummy variables is zero, the influence of a default group affects the magnitude and the sign of ASC in the specification of a model. In addition, the value of a dummy variable seems to influence the relative preference of travel mode in this research. The greater the positive value of a dummy variable, the greater the use of cars. In contrast, the greater the negative value of a dummy variable, the greater the use of PT.

The underlying assumption of additional segmentation variables is that one segmented group whose perception and attitude is different from the other segmented groups may differently choose travel mode and represent the sensitivity to the level of the MSP differently.

7.6.3. Results of segmentation: attitude about "congestion problems are very severe. "

7.6.3.1. Application of the segmentation method using dummy variables

In **Table 7-12**, the ρ^2 of the segmented model (0.334) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude for the coefficients of MSP in the segmented model are the same as those of the default model. Since the sign of ASC (β_0) is negative, it can be inferred that individuals prefer the use of PT if all other attributes remain the same. In this case, the introduction of dummy variables in the specification may cause the increase of PT usage. The coefficient of ASC (β_0) is statistically significant at the 99% level of confidence since the absolute t-value (– 2.7115) is greater than 2.57.

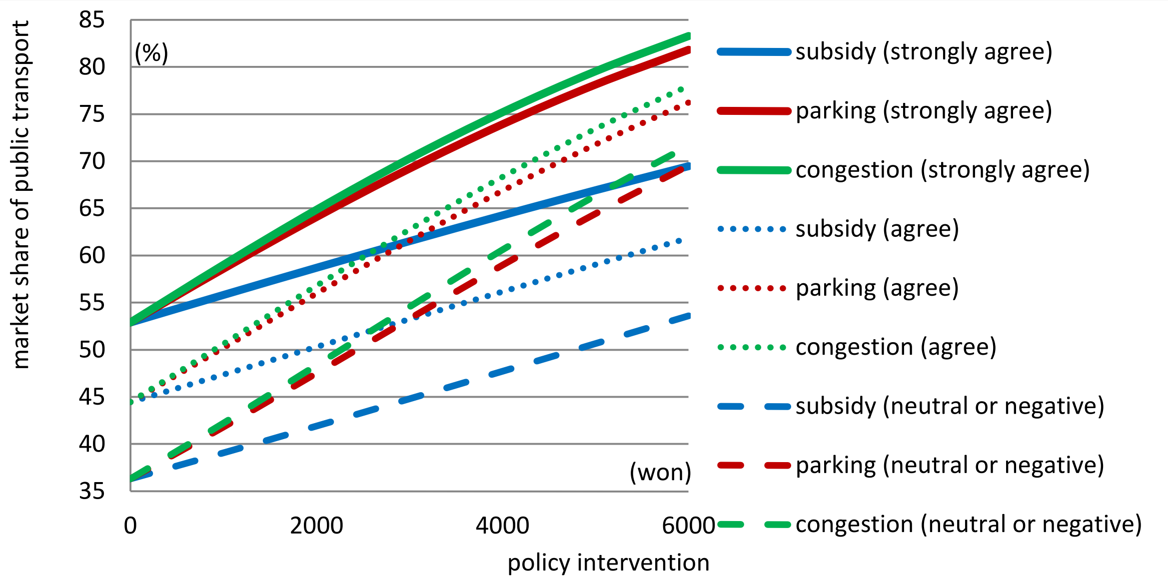
Table 7-12. The coefficients of a segmented model using a dummy variable (Congestion consciousness)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**-0.1160**	**-2.7115****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1177**	**12.7324****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2314**	**-23.5454****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2482**	**-29.5942****
Dummy consciousness of congestion severity 1 (strongly agree:0, agree:1)	$\beta_{congestion\ 1}$			**0.3393**	**8.0672****
Dummy consciousness of congestion severity 2 (strongly agree:0, neutral or others:1)	$\beta_{congestion2}$			**0.6783**	**10.9992****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8263.502	
ρ^2		0.324		**0.334**	
Number of observations		678		674	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

If a respondent agrees with the statement that "congestion problems are very severe during the morning peak" (moderate positive group), the value of the dummy attribute will be one. In this case, the value of the coefficient (0.3393) is multiplied by the value of the attribute (1) (= 0.3393×1). Thus, the utility value of the dummy variable will be 0.3393. Next, if a respondent has a neutral or negative opinion about that statement (negative group), the value of the dummy attribute will be one. In this case, the value of the coefficient (0.6783) is multiplied by the value of the attribute (1) (= 0.6783×1). The utility value of the dummy variable will be 0.6783. Lastly, if a respondent agrees strongly with that statement (strong positive group), the value of the dummy attribute will be zero. In addition, the positive dummy variables will contribute to the increase of utility of car use since the dummy variables are placed in the utility function of car use. All in all, since the magnitude of coefficient of the negative group is greater than that of the moderate positive group, it is expected that the negative group tends to prefer the use of cars rather than the other positive groups. That is, people who deny the severity of congestion problems would be more likely to like the use of a car. As indicated in **Figure 7-4**, the strong positive group is more likely to use PT than the other groups. This result is logical and predictable.

Figure 7-4. The modal shift probability curves in a segmented model using dummy variables (Congestion consciousness)



7.6.3.1. Application of the segmentation method using separate data of the segmented groups

In **Table 7-13**, the coefficient value β_1 (0.0722) for the strong positive group is lower than that of the moderate positive group (0.1645) or the negative group (0.2298). It implies that the modal shift effects of PT commuting cost subsidies for the strong positive group are weaker than the other groups.

Table 7-13. The coefficients of segmented models using separate data (Congestion consciousness)

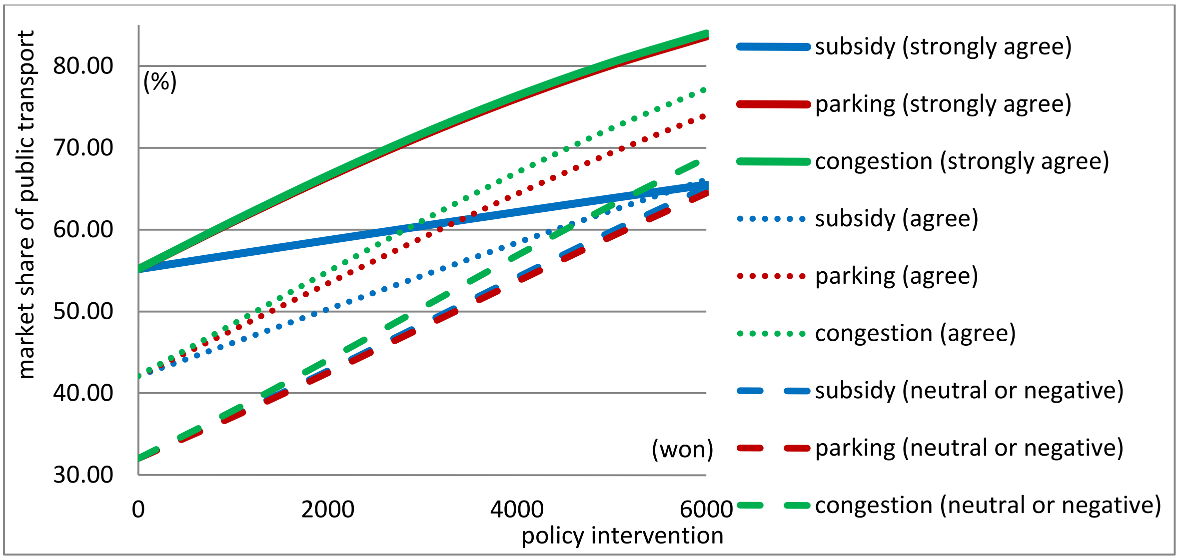
Coefficient		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**-0.2067**	**-3.9172****	**0.3183**	**4.8030****	**0.7527**	**6.2250****
PT cost subsidy	β_1	**0.0722**	**6.1836****	**0.1645**	**10.0995****	**0.2298**	**7.0218****
Additional parking fee	β_2	**-0.2372**	**-17.2401****	**-0.2276**	**-13.9428****	**-0.2248**	**-8.0106****
Congestion charge	β_3	**-0.2415**	**-20.6059****	**-0.2565**	**-18.3677****	**-0.2569**	**-10.7695****
L(0)		-6948.107		-4160.269		-1223.405	
$L(\widehat{\beta})$		-4358.225		-2933.032		-953.8845	
ρ^2		0.3727		0.2950		0.2203	
Number of observations		417		269		77	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

The slope of the modal shift probability curve varies according to each MSP for each segmented group. An interesting point is that the modal shift effects of PT commuting cost subsidies for the strong positive group, which agrees strongly with the severity of congestion, are very much lower than the other groups (see **Figure 7-5**).

Figure 7-5. The modal shift probability curves in the segmented models using separate data (Congestion consciousness)



Detailed results of segmentation analysis with other attitudinal variables are attached to **Appendix 8**.

7.7. Overview of Segmentation Results with Socio-demographic Variables and Attitudinal Variables

7.7.1. Segmentation results of socio-demographic variables in the segmented model using dummy variables

Table 7-14 shows the market share of PT and the modal shift rate of MSP in regard to the socio-demographic variables in the segmentation method using dummy variables. As shown in **Table 7-14**, in terms of the market share of PT at present, people who live in Seoul, the males, the younger, the less educated worker, people who work in the administrative or clerical sector, the poor, people who do not have a child are higher than the other groups. People who have only one car, people who take more than 41 minutes as commute time from home to work when they use a car, people whose main main mode is other mode aside from the car, and people whose main use of a car is other purposes except for commuting to/from work or school are also higher than the other groups. In addition, people who live in the area far more than 20km to workplace express a higher market share of PT than people who live in the area far less than 20km to the workplace. It can be inferred that they prefer the use of PT rather than the use of a car so far.

Since the values (starting point) of market share of PT for each segmented variable are different at the current state (e.g. region (in Seoul): 49.17%, gender (male): 49.42%), objective comparison of the modal shift effect of MSP for each segmented group between before and after implementation of the MSP cannot be provided. Conversely, 'the change rate of the market share of PT based on the current state' can offer more objective information on how much the market share of PT is changed according to the increase of level of a specific MSP (Han, 2007). As shown in **Table 7-14** (see the first row and last column), increasing modal shift rates of MSP based on the current state with the one group (e.g. congestion charges for region factor: 71.70%, see number in parenthesis) are higher than the other group (64.61%) at the intense level of MSP (6,000 won) whereas the values of the market share of PT are lower (78.86%) than the other group (80.94%). However, through the increasing modal shift rate of MSP based on the current state, the degree of the modal shift effects of the MSP can be understood more objectively.

In addition, without exception, the greatest level of the modal shift would be achieved by the introduction of congestion charges, with additional parking fees the next most effective, and the lowest level of the modal shift generated by the PT commuting cost subsidies. In particular, since the coefficient of the dummy variable related to whether a commuter has a child or children who commute to schools, nurseries or infant caring facilities or not is statistically insignificant (see **Appendix Table 7-13**), the segmentation of this variable may be meaningless in terms of statistics.

Table 7-14. The market share of PT and the increasing modal shift rate of MSP in regard to the socio-demographic variables in the segmentation method of using dummy variables (unit: %)

Variable	Segment group	Present	Subsidy		Parking		Congestion	
		₩0	₩3,000	₩6,000	₩3,000	₩6,000	₩3,000	₩6,000
Region (home)	In Seoul	**49.17**	58.45 (18.87)	67.17 (36.61)	65.78 (33.78)	79.25 (61.18)	66.96 (36.18)	**80.94** (64.61)
	Outside of Seoul	45.93	55.27 (20.34)	64.25 (39.89)	62.80 (36.73)	77.04 (67.73)	64.03 (39.41)	78.86 (**71.70**)
Gender	Male	**49.42**	58.16 (17.69)	66.41 (34.38)	65.97 (33.49)	79.37 (60.60)	67.11 (35.80)	**81.00** (63.90)
	Female	42.19	50.94 (20.74)	59.63 (41.34)	59.16 (40.22)	74.18 (75.82)	60.39 (43.14)	76.10 (**80.37**)
Age	20-30s	**60.55**	69.09 (14.10)	76.49 (26.33)	75.71 (25.04)	86.36 (42.63)	76.63 (26.56)	**87.51** (44.53)
	40s	41.35	50.65 (22.49)	59.91 (44.89)	58.88 (42.39)	74.42 (79.98)	60.1 (45.34)	76.29 (84.50)
	50s+	37.65	46.78 (24.25)	56.14 (49.11)	55.09 (46.32)	71.36 (89.54)	56.33 (49.61)	73.37 (**94.87**)
Education	Below university	**56.44**	64.84 (14.88)	72.41 (28.30)	72 (27.57)	83.62 (48.16)	73.06 (29.45)	**85.02** (50.64)
	Undergraduate	49.71	58.45 (17.58)	66.69 (34.16)	66.24 (33.25)	79.57 (60.07)	67.42 (35.63)	81.24 (63.43)
	Postgraduate	43.57	52.36 (20.17)	60.99 (39.98)	60.52 (38.90)	75.26 (72.73)	61.78 (41.79)	77.18 (**77.14**)
Occupation	Other sector	42.3	51.42 (21.56)	60.44 (42.88)	59.45 (40.54)	74.58 (76.31)	60.69 (43.48)	76.48 (**80.80**)
	Administration sector	**55.98**	64.74 (15.65)	72.61 (29.71)	71.78 (28.22)	83.58 (49.30)	72.82 (30.08)	**84.95** (51.75)
Income	Up to ₩5,000,000	**56.97**	65.57 (15.10)	73.25 (28.58)	72.73 (27.66)	84.31 (47.99)	73.79 (29.52)	**85.68** (50.39)
	₩5,000,001~7,000,000	44.46	53.51 (20.36)	62.34 (40.22)	61.72 (38.82)	76.45 (71.95)	62.98 (41.66)	78.34 (76.20)
	More than ₩7,000,001	37.01	45.8 (23.75)	54.85 (48.20)	54.2 (46.45)	70.45 (90.35)	55.54 (50.07)	72.64 (**96.27**)
Child	Not Having child	**48.88**	57.56 (17.76)	65.79 (34.59)	65.46 (33.92)	78.98 (61.58)	66.66 (36.37)	**80.7** (65.10)
	Having child	47.54	56.25 (18.32)	64.58 (35.84)	64.24 (35.13)	78.08 (64.24)	65.46 (37.69)	79.85 (**67.96**)
Distance of commute	Less than 10km	45.86	58.05 (26.58)	69.33 (51.18)	63.04 (37.46)	77.45 (68.88)	64.22 (40.03)	79.18 (72.66)
	10.1km ~ 20km	41.27	53.44 (29.49)	65.22 (58.03)	58.59 (41.97)	74.02 (79.36)	59.82 (44.95)	75.93 (**83.98**)
	More than 20km	**51.05**	63.01 (23.43)	73.57 (44.11)	67.74 (32.69)	80.87 (58.41)	68.85 (34.87)	**82.40** (61.41)
Car number	1	**52.34**	61.58 (17.65)	70.05 (33.84)	68.83 (31.51)	81.62 (55.94)	69.97 (33.68)	**83.18** (58.92)
	2 or more	36.17	45.26 (25.13)	54.68 (51.18)	53.26 (47.25)	69.62 (92.48)	54.59 (50.93)	71.84 (**98.62**)
Car commuting Time	Up to 40 minutes	39.69	48.61 (22.47)	57.61 (45.15)	57.5 (44.87)	73.54 (85.29)	58.8 (48.15)	75.57 (**90.40**)
	More than 41 minutes	**44.12**	53.15 (20.47)	61.98 (40.48)	61.87 (40.23)	76.93 (74.37)	63.13 (43.09)	**78.77** (78.54)
Main commute Mode	Car	20.19	27.78 (37.59)	36.92 (82.86)	36.39 (80.24)	56.41 (179.40)	37.7 (86.73)	59.14 (**192.92**)
	Other	**65.41**	74.2 (13.44)	81.39 (24.43)	81.05 (2391)	90.63 (38.56)	81.89 (25.19)	**91.54** (39.95)

Main use of a car	Commute to/from work or school	27.97	36.72 (31.28)	46.45 (66.07)	45.31 (61.99)	63.88 (128.39)	46.78 (67.25)	66.56 (**137.97**)
	Other	**63.97**	72.63 (13.54)	79.87 (24.86)	79.12 (23.68)	88.99 (39.11)	80.08 (25.18)	**90.1** (40.85)

* The values in parenthesis ( ) mean the change rate of modal shift from car to PT according to the change of level of MSP based on the current state.
$\left(\frac{\textit{market share of the PT after the implementation of the MSP}\ \%}{\textit{market share of the PT before the impelemtatin of the MSP}\ \%} - 1\right) \times 100\%$
* The highest value in each segment or each variable is highlighted.
* The yellow coloured blocks mean the highest modal shift rate of PT based on the current state.
* The pink coloured blocks mean a segmented coefficient related to the dummy variable is statistically insignificant.

7.7.2. Segmentation results of socio-demographic variables in the segmented model using separate data of segmented groups

Table 7-15 illustrates the market share of PT and modal shift rate of MSP in regard to the socio-demographic variables in the segmentation method using separate data of segmented groups. The general trends of the market share of PT at present are similar to those of **Table 7-14**. However, there are two exceptions. That is, the market share of PT with people who live outside of Seoul is a little higher than that of people who live in Seoul. In addition, the market share of PT with people who are in their 50s or more is higher than that of people who are in their 40s. As a result, in terms of the order of the market share of PT at the present state, this result is different from those of **Table 7-14**. In terms of judging the position of the intercept (i.e. the relative mode preferences of segmented groups), the segmentation model using dummy variables, which has the same ASC and the same coefficients of MSP variables, seems to be better than the segmentation models using separate data.

In many cases, the greatest level of modal shift would be achieved by the introduction of congestion charges, with additional parking fees the next most effective, and the lowest level of modal shift generated by PT commuting cost subsidies. However, there are several exceptions. For people who are in their 20-30s, people who work in administrative and clerical sector, and people whose purpose of main use of a car are others except for commuting to/from work or school, the modal shift effects of additional parking fees are stronger than congestion charges. In addition, for the female, modal shift effects of PT commuting cost subsidies are stronger than those of additional parking fees. In particular, since the coefficient of PT commuting cost subsidies with people who are in their 50s or more is statistically insignificant (see **Appendix Table 7-4**), this coefficient should be excluded in the interpretation of the modal shift effects.

In addition, the modal shift effect of people living outside of Seoul, the male, the elderly, the middle educated people, the middle income group, and people who take more than 41 minutes as commute time when they use a car, concerning PT commuting cost subsidies, is very much lower than the other groups (see **Figure 7-2**, **Appendix Figure 7-2**, **Appendix Figure 7-4**, **Appendix Figure 7-6**, **Appendix Figure 7-10**, and **Appendix Figure 7-18**).

Table 7-15. The market share of PT and increasing modal shift rate of MSP in regard to the socio-demographic variables in the segmentation method of using separate data (unit: %)

Variable	Segment group	Present	Subsidy		Parking		Congestion	
		₩0	₩3,000	₩6,000	₩3,000	₩6,000	₩3,000	₩6,000
Region (home)	In Seoul	46.91	60.32 (28.59)	72.34 (54.21)	63.76 (35.92)	77.80 (65.85)	65.03 (38.63)	79.65 (**69.79**)
	Outside of Seoul	**48.23**	54.67 (13.35)	60.95 (26.37)	64.93 (34.63)	78.63 (63.03)	66.04 (36.93)	**80.23** (66.35)
Gender	Male	**49.61**	57.24 (15.38)	64.54 (30.09)	66.47 (33.99)	79.97 (61.20)	67.59 (36.24)	**81.55** (64.38)
	Female	40.91	56.66 (38.50)	71.17 (73.97)	56.05 (37.01)	70.14 (71.45)	57.47 (40.48)	72.42 (**77.02**)
Age	20-30s	**55.80**	71.43 (28.01)	83.20 (49.10)	73.30 (31.36)	**85.65** (53.49)	72.81 (30.48)	85.03 (52.38)
	40s	38.49	51.16 (32.92)	63.68 (65.45)	56.66 (47.21)	73.19 (90.15)	57.63 (49.73)	74.12 (**92.57**)
	50s+	47.30	46.85 (-0.95)	46.40 (-1.90)	61.13 (29.24)	73.37 (55.12)	65.48 (38.44)	80.03 (69.20)
Education	Below university	**59.35**	69.14 (16.50)	77.46 (30.51)	71.68 (20.78)	81.43 (37.20)	73.35 (23.59)	**83.85** (41.28)
	Undergraduate	51.24	58.11 (13.41)	64.68 (26.23)	67.42 (31.58)	80.30 (56.71)	68.48 (33.65)	81.79 (59.62)
	Postgraduate	39.55	52.41 (32.52)	64.95 (64.22)	57.54 (45.49)	73.73 (86.42)	58.92 (48.98)	75.87 (**91.83**)
Occupation	Other sector	45.13	51.83 (14.85)	58.47 (29.56)	60.89 (34.92)	74.67 (65.46)	63.03 (39.66)	77.94 (**72.70**)
	Administration sector	**50.53**	65.35 (29.33)	77.69 (53.75)	69.36 (37.26)	**83.38** (65.01)	68.91 (36.37)	82.79 (63.84)
Income	Up to ₩5,000,000	**55.23**	67.39 (22.02)	77.58 (40.47)	71.49 (29.44)	83.60 (51.37)	71.71 (29.84)	**83.89** (51.89)
	₩5,000,001~7,000,000	44.58	48.73 (9.31)	52.89 (18.64)	62.92 (41.14)	78.16 (75.33)	65.97 (47.98)	82.37 (**84.77**)
	More than ₩7,000,001	38.77	49.06 (26.54)	59.44 (53.31)	54.70 (41.09)	69.72 (79.83)	55.32 (42.69)	70.77 (82.54)
Child	Not Having child	**50.68**	63.37 (25.04)	74.44 (46.88)	65.69 (29.62)	78.10 (54.10)	66.67 (31.55)	79.56 (56.99)
	Having child	45.67	53.30 (16.71)	60.78 (33.09)	64.06 (40.27)	79.08 (73.16)	65.52 (43.46)	**81.11** (**77.60**)
Distance of commute	Less than 10km	49.17	61.95 (25.99)	73.27 (49.01)	63.36 (28.86)	75.55 (53.65)	65.33 (32.87)	78.59 (59.83)
	10.1km ~ 20km	38.55	50.90 (32.04)	63.14 (63.79)	57.95 (50.32)	75.18 (95.02)	58.58 (51.96)	76.13 (**97.48**)
	More than 20km	**51.55**	63.06 (22.33)	73.26 (42.11)	68.05 (32.01)	81.00 (57.13)	69.17 (34.18)	**82.55** (60.14)
Car number	1	**50.17**	62.55 (24.68)	73.49 (46.48)	67.20 (33.94)	80.65 (60.75)	68.32 (36.18)	**82.20** (63.84)
	2 or more	39.55	44.70 (13.02)	49.98 (26.37)	56.31 (42.38)	71.75 (81.42)	57.73 (45.97)	74.04 (**87.21**)
Car commuting Time	Up to 40 minutes	40.82	52.88 (29.54)	64.62 (58.30)	56.70 (38.90)	71.32 (74.72)	58.12 (42.38)	73.64 (80.40)

	More than 41 minutes	**42.71**	49.74 (16.46)	56.78 (32.94)	62.46 (46.24)	78.78 (84.45)	63.62 (48.96)	**80.39 (88.22)**
Main commute Mode	Car	21.30	26.79 (25.77)	33.09 (55.35)	38.05 (78.64)	58.23 (173.38)	39.55 (85.68)	61.27 (**187.65**)
	Other	**62.92**	77.58 (23.30)	86.29 (37.14)	79.25 (25.95)	89.57 (42.36)	79.91 (27.00)	**90.31** (43.53)
Main use of a car	Commute to/from work or school	27.92	35.31 (26.47)	43.46 (55.66)	45.50 (62.97)	64.27 (130.19)	47.75 (71.02)	68.30 (**144.63**)
	Other	**63.47**	75.01 (18.18)	83.83 (32.08)	78.56 (23.78)	**88.54** (39.50)	78.46 (23.62)	88.42 (39.31)

* The values in parenthesis ( ) mean the change rate of modal shift from car to PT according to the change of level of MSP based on the current state.
$\left(\frac{\text{market share of the PT after the implementation of the MSP \%}}{\text{market share of the PT before the impelemtatin of the MSP \%}} - 1\right) \text{X } 100\%$
* The highest value in each segment or each variable is highlighted.
* The yellow coloured blocks mean the highest modal shift rate of PT based on the current state.
* The pink coloured blocks mean a segmented coefficient related to the dummy variable is statistically insignificant.
* The blue coloured letters mean the order of the modal shift probability different from the general order of the modal shift probability (i.e. PT subsidy < parking fee < congestion charge).
* The blue coloured blocks mean the highest modal shift probability that changes the general order of the modal shift probability (i.e. PT subsidy < parking fee < congestion charge).

7.7.3. Segmentation results of attitudinal variables in the segmented model using dummy variables

Table 7-16 shows the market share of PT and the modal shift rate of MSP in regard to attitudinal variables in the segmentation method using dummy variables. As shown in **Table 7-16**, in terms of market share of PT at present, people who agree strongly with the severity of traffic congestion, the importance of PT use for environmental protection, the usefulness of PT usage for their health, the importance of time, and the importance of cost in determining commuting are higher than other groups. In addition, people who disagree with the freedom of mode choices from government regulation and people who disagree with the importance of convenience in determining commuting are higher than the other groups. It can be inferred that they prefer the use of PT rather than the use of a car so far.

In addition, without exception, the greatest level of modal shift would be achieved by the introduction of congestion charges, with additional parking fees the next greatest effective, and the lowest level of modal shift generated by PT commuting cost subsidies. In particular, since the coefficient of the dummy variable related to people who agree (mildly) with the statement that “the freedom of choosing a travel mode should not be restricted by government regulation” is statistically insignificant (see **Appendix Table 8-5**), this coefficient should be excluded in the interpretation of modal shift effects.

Table 7-16. The market share of PT and the increasing the modal shift rate of MSP in regard to the attitudinal variables in the segmentation method of using dummy variables (unit: %)

Variable	Segment group	Present	Subsidy		Parking		Congestion	
		₩0	₩3,000	₩6,000	₩3,000	₩6,000	₩3,000	₩6,000
Congestion Severity	Strongly Agree	**52.9**	61.52 (16.29)	69.47 (31.32)	69.22 (30.85)	81.82 (54.67)	70.28 (32.85)	**83.27** (57.41)
	Agree	44.44	53.24 (19.80)	61.84 (39.15)	61.56 (38.52)	76.23 (71.53)	62.75 (41.20)	78 (75.52)
	Neutral or Others	36.3	44.79 (23.39)	53.59 (47.63)	53.29 (46.80)	69.55 (91.60)	54.54 (50.25)	71.64 (**97.36**)
Environmental Consciousness	Strongly Agree	**64.77**	72.57 (12.04)	79.19 (22.26)	79.06 (22.06)	88.58 (36.76)	79.91 (23.38)	**89.59** (38.32)
	Agree	38.68	47.58 (23.01)	56.64 (46.43)	56.44 (45.92)	72.69 (87.93)	57.72 (49.22)	74.71 (93.15)
	Neutral or Others	35.79	44.50 (24.34)	53.57 (49.68)	53.38 (49.15)	70.17 (96.06)	54.67 (52.75)	72.30 (**102.01**)
Healthy Consciousness	Strongly Agree	**61.20**	69.65 (13.81)	76.95 (25.74)	76.12 (24.38)	86.56 (41.44)	76.99 (25.80)	**87.66** (43.24)
	Agree	42.40	51.71 (21.96)	60.91 (43.66)	59.8 (41.04)	75.04 (76.98)	60.97 (43.80)	76.82 (**81.18**)
	Neutral or Others	43.45	52.79 (21.50)	61.93 (42.53)	60.83 (40.00)	75.83 (74.52)	61.99 (42.67)	77.58 (78.55)
Freedom from governmental regulation	Strongly Agree	43.44	52.66 (21.22)	61.69 (42.01)	60.75 (39.85)	75.73 (74.33)	61.97 (42.66)	77.56 (78.55)
	Agree	41.81	50.99 (21.96)	60.1 (43.75)	59.15 (41.47)	74.48 (78.14)	60.38 (44.42)	76.38 (**82.68**)
	Neutral or Others	**57.71**	66.4 (15.06)	74.1 (28.40)	73.33 (27.07)	84.71 (46.79)	74.32 (28.78)	**86** (49.02)
Importance of convenience	Strongly Agree	44.27	53.39 (20.60)	62.3 (40.73)	61.44 (38.78)	76.18 (72.08)	62.6 (41.41)	77.9 (**75.97**)
	Agree	46.55	55.68 (19.61)	64.44 (38.43)	63.6 (36.63)	77.81 (67.15)	64.73 (39.05)	79.45 (70.68)
	Neutral or Others	**70.47**	77.49 (9.96)	83.24 (18.12)	82.73 (17.40)	90.57 (28.52)	83.41 (18.36)	**91.38** (29.67)
Importance of time	Strongly Agree	**50.59**	59.46 (17.53)	67.75 (33.92)	67.27 (32.97)	80.49 (59.10)	68.31 (35.03)	**81.95** (61.99)
	Agree	45.71	54.67 (19.60)	63.34 (38.57)	62.83 (37.45)	77.24 (68.98)	63.93 (39.86)	78.87 (72.54)
	Neutral or Others	43.79	52.74 (20.44)	61.51 (40.47)	60.99 (39.28)	75.84 (73.19)	62.12 (41.86)	77.55 (**77.10**)
Importance of cost	Strongly Agree	**64.95**	73.02 (12.42)	79.81 (22.88)	79.45 (22.32)	88.96 (36.97)	80.28 (23.60)	**89.94** (38.48)
	Agree	50.04	59.4 (18.71)	68.11 (36.11)	67.63 (35.15)	81.33 (62.53)	68.76 (37.41)	82.86 (65.59)
	Neutral or Others	29.82	38.29 (28.40)	47.53 (59.39)	46.98 (57.55)	64.89 (117.61)	48.28 (61.90)	67.21 (**125.39**)

* The values in parenthesis ( ) mean the change rate of modal shift from car to PT according to the change of level of MSP based on the current state.

$$\left(\frac{\textit{market share of the PT after the implementation of the MSP}\ \%}{\textit{market share of the PT before the impelemtatin of the MSP}\ \%} - 1\right) \text{X } 100\%$$

* The highest value in each segment or each variable is highlighted.

* The yellow coloured blocks mean the highest modal shift rate of PT based on the current state.

* The pink coloured blocks mean a segmented coefficient related to the dummy variable is statistically insignificant.

7.7.4. Segmentation results of attitudinal variables in the segmented model using separate data of segmented groups

Table 7-17 illustrates the market share of PT and the modal shift rate of MSP in regard to attitudinal variables in the segmentation method using separate data of segmented groups. The general trends of the market share of PT at present are similar to those of **Table 7-16**. However, there is one exception. That is, market share of PT (47.93%) with people who agree (mildly) with the importance of time in determining commuting is a little higher than that (47.55%) of people who agree strongly with the statement. As a result, in terms of the order of the market share of PT at the present state, this result is different from that of **Table 7-16**. In terms of judging the relative mode preferences of segmented groups through the position of the intercept, the segmentation model using dummy variables, which has the same ASC and the same coefficients of MSP variables, seems to be better than the segmentation method using separate data of segmented groups.

In many cases, the greatest level of modal shift would be achieved by the introduction of congestion charges, with additional parking fees the next most effective, and the lowest level of modal shift generated by PT commuting cost subsidies. However, there are several exceptions. For people who disagree (mildly) with the importance of convenience and people who disagree (mildly) with the importance of time in determining commuting, the modal shift effects of additional parking fees are stronger than those of congestion charges. In addition, for people who disagree with congestion severity, people who agree strongly with the importance of PT use for environmental protection, and people who agree strongly with the usefulness of PT use for their health, the modal shift effects of PT commuting cost subsidies are stronger than those of additional parking fees.

In addition, the modal shift effect of people who agree strongly with the statement that "congestion problems are very severe during the morning peak.", people who agree (mildly) with the statement that "the use of PT is important to reduce global warming and to protect the environment.", people who disagree with the statement that "the freedom of choosing a travel mode should not be restricted by government regulation.", people who agree (mildly) with the statement that "convenience is a very important factor in determining commuting.", people who agree (mildly) with the statement that "time is a very important factor in determining commuting.", and people who disagree with the statement that "cost is a very important factor in determining commuting." concerning PT commuting cost subsidies is very much lower than the other groups (see **Figure 7-5**, **Appendix Figure 8-2**, **Appendix Figure 8-4**, **Appendix Figure 8-6**, **Appendix Figure 8-8**, and **Appendix Figure 8-12**).

Table 7-17. The market share of PT and the increasing modal shift rate of MSP in regard to the attitudinal variables in the segmentation method of using separated data (unit: %)

Variable	Segment group	Present	Subsidy		Parking		Congestion	
		₩0	₩3,000	₩6,000	₩3,000	₩6,000	₩3,000	₩6,000
Congestion severity	Strongly Agree	**55.15**	60.43 (9.57)	65.47 (18.71)	71.47 (29.59)	83.62 (51.62)	71.73 (30.06)	**83.97** (52.26)
	Agree	42.11	54.37 (29.11)	66.12 (57.02)	59.01 (40.13)	74.03 (75.80)	61.09 (45.07)	77.22 (83.38)
	Neutral or Others	32.02	48.42 (51.22)	65.16 (103.50)	48.04 (50.03)	64.48 (101.37)	50.45 (57.56)	68.76 (**114.74**)
Environmental consciousness	Strongly Agree	**57.57**	75.46 (31.08)	87.45 (51.90)	74.33 (29.11)	86.07 (49.50)	75.90 (31.84)	**87.97** (52.81)
	Agree	41.35	46.66 (12.84)	52.06 (25.90)	58.90 (42.44)	74.45 (80.05)	60.16 (45.49)	76.38 (84.72)
	Neutral or Others	37.33	45.93 (23.04)	54.79 (46.77)	54.54 (46.10)	70.73 (89.47)	54.89 (47.04)	71.32 (**91.05**)
Healthy consciousness	Strongly Agree	**60.86**	74.96 (23.17)	85.22 (40.03)	73.20 (20.28)	82.75 (35.97)	75.44 (23.96)	**85.85** (41.06)
	Agree	45.88	48.65 (6.04)	51.43 (12.10)	63.67 (38.78)	78.37 (70.82)	64.66 (40.93)	79.80 (73.93)
	Neutral or Others	39.62	53.04 (33.87)	66.03 (66.66)	58.40 (47.40)	75.03 (89.37)	58.86 (48.56)	75.73 (**91.14**)
Freedom from governmental regulation	Strongly Agree	48.61	57.69 (18.68)	66.28 (36.35)	62.82 (29.23)	75.12 (54.54)	63.23 (30.08)	75.77 (55.87)
	Agree	39.16	51.32 (31.05)	63.33 (61.72)	56.67 (44.71)	72.66 (85.55)	58.64 (49.74)	75.74 (**93.41**)
	Neutral or Others	**56.89**	61.53 (8.16)	65.96 (15.94)	74.89 (31.64)	87.08 (53.07)	75.64 (32.96)	**87.95** (54.60)
Importance of convenience	Strongly Agree	44.31	55.00 (24.13)	65.25 (47.26)	60.77 (37.15)	75.09 (69.47)	62.05 (40.04)	77.06 (**73.91**)
	Agree	48.66	55.02 (13.07)	61.21 (25.79)	65.21 (34.01)	78.76 (61.86)	66.48 (36.62)	80.59 (65.62)
	Neutral or Others	**56.85**	74.94 (31.82)	87.16 (53.32)	79.27 (39.44)	**91.73** (61.35)	78.52 (38.12)	91.03 (60.12)
Importance of time	Strongly Agree	47.55	59.27 (24.65)	70.02 (47.26)	65.24 (37.20)	79.53 (67.26)	66.64 (40.15)	**81.49** (71.38)
	Agree	**47.93**	53.39 (11.39)	58.77 (22.62)	64.86 (35.32)	78.73 (64.26)	65.91 (37.51)	80.24 (67.41)
	Neutral or Others	47.07	59.60 (26.62)	70.99 (50.82)	61.25 (30.13)	73.76 (56.70)	61.12 (29.85)	73.54 (56.24)
Importance of cost	Strongly Agree	**58.80**	73.90 (25.68)	84.89 (44.37)	75.97 (29.20)	87.50 (48.81)	77.60 (31.97)	**89.38** (52.01)
	Agree	39.11	53.82 (37.61)	67.89 (73.59)	63.21 (61.62)	82.13 (110.00)	64.24 (64.25)	83.40 (**113.24**)
	Neutral or Others	43.44	47.00 (8.20)	50.40 (16.02)	55.20 (27.07)	66.23 (52.46)	56.52 (30.11)	68.57 (57.85)

* The values in parenthesis ( ) mean the change rate of modal shift from car to PT according to the change of level of MSP based on the current state.

$$\left(\frac{\text{market share of the PT after the implementation of the MSP }\%}{\text{market share of the PT before the impelemtatin of the MSP }\%} - 1\right) \times 100\%$$

* The highest value in each segment or each variable is highlighted.
* The yellow coloured blocks mean the highest modal shift rate of PT based on the current state.
* The blue coloured letters mean the order of the modal shift probability different from the general order of the modal shift probability (i.e. PT subsidy < parking fee < congestion charge).
* The blue coloured blocks mean the highest modal shift probability that changes the general order of the modal shift probability (i.e. PT subsidy < parking fee < congestion charge).

7.8. Summary

In order to deeply understand the modal shift effects of MSP across various groups, to obtain more accurate predictions about the behaviour of categorical groups, and to identify intrinsic or relative mode preferences of segmented groups, two types of segmented choice models are developed: segmentation models using dummy variables and segmentation models using separate data for segmented groups. In addition, to keep the standard errors for a model acceptably small, the segmentation models are limited to one segment variable per model, with a maximum of three categories (Wardman, 1988). In this research, segmentation variables are composed of twelve socio-demographic variables and seven attitudinal variables. In addition, reviews on the sample size and the correlation analysis of segmented variables are conducted.

Through segmentation models using dummy variables, the ρ^2 of the segmented models can be compared with that of the default model in order to assess the validity of the segmented models. As a result, all the segmented models are better than the default model in terms of the magnitude of the ρ^2. In addition, by using this type of models, the relative preference of travel mode across the segmented group can be understood. That is, the position of intercepts for modal shift probability curves of segmented groups is compared in order to more accurately understand the relative mode preferences at the current state.

Meanwhile, through segmentation models using separate data of segmented groups, the modal shift effects of the MSPs for segmented groups and the patterns of intrinsic mode preferences of segmented groups can be measured and grasped. Through this type of models, the question about which group is more sensitive to the level of the MSPs is answered. As a result, it is discovered that the modal shift effects of PT commuting cost subsidies for some segmented groups are very much lower than the other MSPs.

In particular, an interesting finding is that besides socio-economic factors, attitudinal factors affect the choice of travel mode substantially. The result provides the necessity of the introduction of informative measures or educational measures for more effective modal shifts.

Chapter 8. Equity Impact Analysis of Modal Shift Policies

8.1. Introduction

The purpose of this chapter is to measure the change in consumer welfare according to the implementation of MSP and to investigate whether an MSP is progressive or regressive. This chapter consists of four more sections. Section 8.2 considers the theoretical background of equity assessment. In this section, much research indicates that if the proportional effect of MSP on income is small, Consumer Surplus (CS) can be a good approximation to the exact Compensating Variation (CV) measure. Section 8.3 represents the calculation method about the consumer welfare. Section 8.4 calculates the Compensating Variation Per Person (CVPP) of MSP and the ratio (π_h) of CVPP to the average income of the income groups through two types of calculation methods in order to grasp the equity effects of MSP. Section 8.5 deals with an equity assessment of various segmented groups.

8.2. Theoretical Background of Equity Assessment

8.2.1. Measurement of equity impact

The welfare impact of the MSP is a main issue how the burden or benefit of the MSP occurs differently according to different income groups. That is, the redistributive effect of policy intervention can be a major issue since regressive public intervention may trigger social conflict and class confrontation. In the perspective of welfare economics, the welfare effect of policy or price as more desirable, less desirable, or indifferent for the social class can be understood. The equity impact of policy intervention can be measured by analysing the change in Consumer Surplus (CS), Equivalent Variation (EV), or Compensating Variation (CV). All in all, although it is difficult to calculate the accurate change of the CS concerning the implementation of an MSP, the equity evaluation of the MSP can be obtained by the calculation of welfare changes.

Rosen and Small (1979) showed how a consumer welfare measure known as CV could be obtained from discrete choice models. Rosen and Small focused on “the study of situations in which consumers face a discrete choice rather than a continuous set of choices” (Rosen and Small, 1979). Rosen and Small used a compensated demand curve for a discrete choice as a measurement of the CV. Although Rosen and Small introduced the concept of CS in terms of the Hicksian demand, Rosen and Small adopted the uncompensated demand as a working approximation (Batley and Ibáñez, 2013). In addition, Rosen and Small demonstrated that "the conventional methods of applied welfare economics can be generalised to handle cases in which discrete choices are involved" (Rosen and Small, 1981, p106). Rosen and Small set forth that by using the estimates of conditional indirect utility function from logit models, the CV could be calculated. Rosen and Small indicated that the amount of the CV about the price of returning to the commuter's utility before the implementation of MSP was the same as that of the commuter's welfare change.

Rosen and Small (1981)'s welfare measure seems to be valid if income effects are not related to the context of the application (Batley and Ibáñez, 2013). In many cases, since the proportion of transport expenditure in income is very small, it can be inferred that income effect on transportation policy is small. In this sense, it can be usually considered that the social surplus derived from Marshallian demand curve can be an approximation of the CV from the Hicksian curve (Batley and Ibáñez, 2013). The CS can be derived from the uncompensated (ordinary) or Marshallian demand curve, which can be normally observable and can be obtained by choice probability, in the discrete process. In contrast, the concept of CV and EV can be derived from the compensated or Hicksian demand curve, which is unobservable in reality. The Marshallian demand curve offers the understanding of the substitution effects only whereas the Hicksian demand curve gives information on substitution and income effects (Jong et al., 2005). Although the CV is a useful concept for exactly assessing welfare change, it requires knowledge of the individual's indifference curves or maps. However, because it is very difficult to obtain the individual's indifference curves or maps in reality, a more practical but less accurate measurement of welfare change, as an alternative, can be used (Lee, 2011b). In other words, as the Hicksian demand curve cannot be observed in practice, an approximate value of CV can be derived from ordinary CS. This approach seems to be a relatively easy and explicit measurement of CS. Therefore, the most commonly used method of assessing welfare change is to measure ordinary CS. According to Jones (1977), the Marshallian Consumer Surplus (MCS) measure can be validly used in the cost-benefit analysis of transport sector. Therefore, it is possible to calculate the welfare benefits of transport intervention through the change in the MCS. Although the CS can be defined as the difference between the price a buyer is willingness to pay and the price he or she ultimately pays, the CS is the most widely used tool in the welfare assessment.

8.2.2. Review of prior measurement of consumer surplus

8.2.2.1. Theoretical background

Willig (1976) offers bounds on the percentage error when people are calculating the welfare indicator Hicksian Consumer Surplus (HCS) by the MCS. This upper and lower bounds depend on the income elasticity of demand and the expenditure share of the good at issue. Willig indicates that the CS is usually a very good approximation to the proper welfare measures[13]. Since this indication offers a good guidance for CV measurement, it can be utilized as a prior assessment.

Hausman (1981) indicates that even when the percentage error in approximating the HCS by the MCS is small, it may be the case that the percentage error in approximating the Hicksian Deadweight Loss (HDL) by Marshallian measure is very large. That is, Hausman offers a gasoline example where the percentage error in approximating the HCS by MCS is 3.2%, and the percentage error in approximating the HDL by Marshallian Deadweight Loss (MDL) is 32%. However, Haveman et al. (1987) indicate that Hausman's calculation in the welfare loss measure and deadweight loss is in error. Haveman et al. show that the deviation between the Marshallian measures and Hicksian measures is just 5.2%. This result proves the validity of Willig's formulae.

In addition, Vives (1987) denotes that if *n* is the number of goods under certain assumptions on preferences and prices, the order of magnitude of individual income derivative of the demand is at

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[13] Willig develops the validity of these rules of thumb:

For a single price change, if $|\overline{\eta}\, A/2m^0| \leq 0.05$, $|\underline{\eta}\, A/2m^0\ | \leq 0.05$, and if $|\ A/m^0| \leq 0.9$,

Then, $\frac{\underline{\eta}|\ A\ |}{2m^0} \leq \frac{\mathrm{CV} - \mathrm{A}}{|\ \mathrm{A}\ |} \leq \frac{\overline{\eta}|\ A\ |}{2m^0} \rightarrow \frac{[1+(1-\underline{\eta})\frac{A}{m^0}]^{1/(1-\underline{\eta})}-1-\frac{A}{m^0}}{|\ \mathrm{A}\ |/\ m^0} \leq \frac{\mathrm{CV} - \mathrm{A}}{|\ \mathrm{A}\ |} \leq \frac{[1+(1-\overline{\eta})\frac{A}{m^0}]^{1/(1-\overline{\eta})}-1-\frac{A}{m^0}}{|\ \mathrm{A}\ |/\ m^0}$

and $\frac{\underline{\eta}|\ A\ |}{2m^0} \leq \frac{\mathrm{A} - \mathrm{EV}}{|\ \mathrm{A}\ |} \leq \frac{\overline{\eta}|\ A\ |}{2m^0} \rightarrow \frac{[1+(1-\underline{\eta})\frac{A}{m^0}]^{1/(1-\underline{\eta})}-1+\frac{A}{m^0}}{|\ \mathrm{A}\ |/\ m^0} \leq \frac{\mathrm{A} - \mathrm{EV}}{|\ \mathrm{A}\ |} \leq \frac{[1+(1-\overline{\eta})\frac{A}{m^0}]^{1/(1-\overline{\eta})}-1+\frac{A}{m^0}}{|\ \mathrm{A}\ |/\ m^0}$

where A = CS area under the demand curve and between the two prices (positive for a price increase and negative for a price decrease)

m^0 = consumer's base income

$\overline{\eta}$ and $\underline{\eta}$ = respectively the largest and smallest values of the income elasticity of demand

The formulae place observable bounds on the percentage errors of approximating the CV or the EV measures with observable A. For example, if the consumer's measured income elasticity of demand is 0.8 and if the surplus area under the demand curve between the old and new prices is 5% of income, then CV is within 2% of the measured CS. That is, when $\underline{\eta}$ = 0.8 and A/m^0= a = 0.05, CV is 2% of the measured CS. This value can easily be obtained by substituting the formula ($\frac{[1-(1-\ \eta)a]]^{1/(1-\eta)}-1+a}{a}$).

(e.g.) $\frac{[1-(1-\eta)a]^{1/(1-\eta)}-1+a}{a} = \frac{[1-(1-0.8)*0.05]^{1/(1-0.8)}-1+0.05}{0.05} = \frac{[0.99]^5-1+0.05}{0.05}$ = 0.019801 ≅ 0.02

The ratio $|\ A\ |/m^0$ can be interpreted as a measure of the proportional change in real income derived from the price change. In many cases, the proportional change will be very small. Measured income elasticities of demand tend to gather closely about 1.0. Therefore, it is expected that $(\underline{\eta}|\ A\ |)/2m^0$ will be small enough to permit substitution of A for the CV or the EV.

most $1/\sqrt{n}$. If only the price of good X changes and we have n goods, the order of the magnitude or the percentage error in approximating the HDL by the MDL ($(\Delta = R)^n/|HDL^n|$) is at most $1/\sqrt{n}$. In the additively separable case, the order of magnitude of the percentage error is $1/n$. This result indicates that as n get large, income effects fade away and the substitution effects remain. For large n the slope of the Marshallian demand function will be close to the slope of Hicksian demand function. Therefore, Vives indicates that the MCS will be a good approximation of the true measure of welfare change, the HCS.

8.2.2.2. The prior assessment of income effect of modal shift policies

Marshall's basic idea is that when the proportion of income spent on a single good is small, the income effects are small. The small size of the income effect has been usually used to justify the MCS approximation to the Hicksian measure and to get downward sloping demand (Vives, 1987; Batley and Ibáñez, 2013). That is, the basic idea of the exact measure of CS is to use the observed market demand curve to derive the unobserved compensated demand curve. Willig (1976) argues that where the change in CS is less than 5%, CS can be a good approximation to the accurate CV measure. In **Table 8-1**, the proportion of transport outlay in Korea is 11.5% of all the consumption expenditure. **Table 8-2** shows that the proportion of outlay related to the direct vehicle usage is 40.3% of consumption expenditure in the transportation sector. Therefore, the proportion of expenditure associating with the direct vehicle usage seems to be only 4.6% of all the consumption expenditure. All in all, the income effect of a new MSP will be a small proportion of the consumption expenditure. Therefore, the MCS can be a good approximation to the exact CV measure in this research.

Table 8-1. The portion of a monthly average consumption expenditure of a household by year

Classification (content /year)	2007	2008	2009	2010	2010(%)
Sum	1,924,277	1,930,922	1,919,595	1,995,304	100%
Food and non-alcoholic beverages	269,556	277,178	257,067	258,256	12.9%
Alcoholic beverages and tobacco	28,447	28,154	26,158	26,789	1.3%
Clothing and footwear	121,778	121,980	116,473	125,974	6.3%
Housing water, electricity, gas and other fuels	183,151	182,605	185,798	197,592	9.9%
Furnishing household equipment and routine maintenance of the house	72,511	67,585	67,127	75,031	3.8%
Health	123,829	123,563	130.217	138,516	6.9%
Transport	**231,897**	**222,220**	**236,709**	**229,697**	**11.5%**
Communication	138,894	139,162	137,112	144,716	7.3%
Recreation and culture	115,900	117,651	119,752	135,830	6.8%
Education	216,027	230,785	240,806	241,419	12.1%
Restaurants and hotels	261,256	263,722	247,358	251,666	12.6%
Miscellaneous goods and services	161,031	156,318	155,017	169,818	8.5%

* Source: Statistics Korea, Korea Statistical Information Service, 2012.

Table 8-2. The portion of a monthly average consumption expenditure of a household in the transportation sector

Classification (content /year)	2007	2008	2009	2010	2010(%)
Total transport	231,897	222,220	236,709	229,697	100%
Car purchase	54,731	52,699	70,289	61,852	26.9%
Other travel vehicle purchase	1,196	1,233	1,269	1,212	0.5%
Vehicle maintenance and repair	14,331	13,204	13,207	13,871	6.0%
Vehicle fuel	**101,204**	**96,890**	**94,755**	**92,538**	**40.3%**
Other individual transport service	**8,056**	**7,236**	**8,870**	**12,231**	**5.3%**
Rail transport	**5,403**	**5,559**	**5,116**	**4,941**	**2.2%**
Land transport	**22,869**	**22,801**	**20,274**	**18,142**	**7.9%**
Other transport	20,996	19,949	20,683	22,691	9.9%
Miscellaneous transport services	3,112	2,650	2,245	2,219	1.0%

* Source: Statistics Korea, Korea Statistical Information Service, 2012.

8.2.3. Marshallian measure and Hicksian measure

Pearce and Nash (1994) explain the relationship between the (conventional) uncompensated demand curve and compensated demand curve. **Figure 8-1** denotes the relationship between the demand curves from an indifference map and the budget constraint. On the above diagram, the vertical axis is depicted from the viewpoint of good X and (Y – P_XX), which implies the amount of monetary income after subtracting outlay on good X. The slope of the budget constraint on the above diagram is equal to P_X in the diagram below. The original budget constraint (GJ) is drawn supposing a monetary income of (0G) and a price of P_{X1}. If the price of good X drops from P_{X1} to P_{X2}, the budget constraint will rotate from (GJ) to (GK) and the demand increases from X_1 to X_2. Meanwhile, if monetary income decreases to a certain degree on the initial indifference curve U_1, the budget constraint corresponding to P_{X2} will be moved from (GK) to the parallel position (IL) on the initial indifference curve U_1. At the same time, in terms of the demand on good X, X_2 will come back to X_3. In this case, X_3 is the demand arising from a price of P_{X2} on the compensated demand curve according to the initial indifference curve U_1. The traditional demand curve (AD) and the compensated demand curve (AB) are illustrated in the diagram below. The meaning of relating distance on the above diagram is as follows (Pearce and Nash, 1994; Lee, 2011b):

* GH = outlay on X at the initial levels of price (P_{X1}) and monetary income (0G) = area 0P_{X1}AX_1

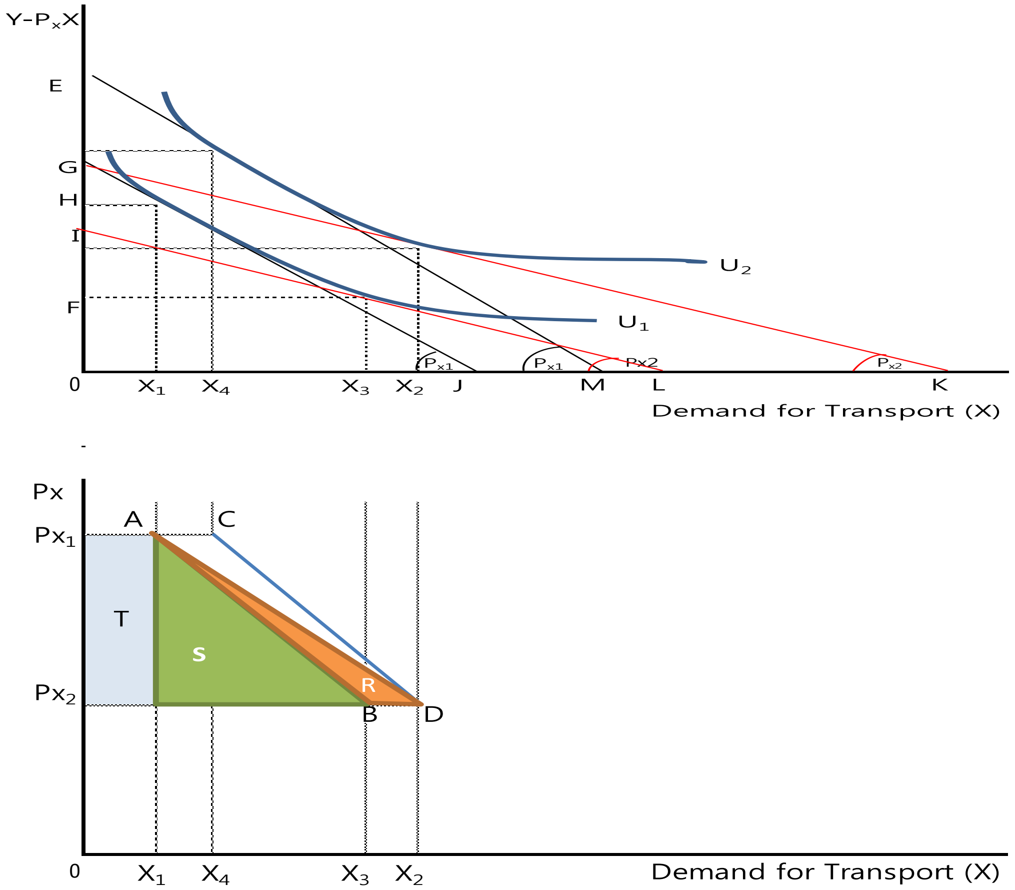
* IF = outlay on X at the final levels of price (P_{X2}) and monetary income (0I) = area 0P_{X2}BX_3

* HF = sum of money which is equal to an increase in good X from X_1 to X_3 on the initial indifference curve U_1 = area X_1ABX_3

* GI = the CV for a price drop from P_{X1} to P_{X2} when the consumer is taken on the initial indifference curve U_1. (GH + IF – HF) = area P_{X1}ABP_{X2}, This is the maximum willingness to pay for the transport intervention.

8.2.4. Compensating variation and Equivalent variation

Figure 8-1. Ordinary consumer surplus, compensating variation and equivalent variation



* Source: Pearce & Nash, 1981, added by a little modification

According to Pearce and Nash (1994), if a price drop from P_{X1} to P_{X2} is considered, it is uncompensated by a change in monetary income in **Figure 8-1**. And then, if an increase in price from P_{X2} to P_{X1} is considered, the CV of the price increase will not be equivalent to that of the original price drop (AD). In this case, a new compensated demand curve (CD) is corresponding to an indifference curve U_2. In order to restore consumer welfare to the indifference curve U_2 at P_{X1}, a parallel shift of the budget constraint to (JM), corresponding to an increase in monetary income of (GE), is needed. This is equal to area $P_{X1}CDP_{X2}$ in the diagram below. This area, known as EV, is a measure of the CS accruing from a price drop. The EV means the minimum increase in monetary income that consumer would be willing to accept to give up the decrease of price. The EV of the corresponding price drop equals the CV of a price increase and vice versa (Pearce and Nash, 1994). In general, for a normal good, the demand curve (CD) corresponding to the higher indifference curve (i.e. the indifference curve U_2) will be to the right of (AB), and then the EV of a price drop will exceed the CV. In general, the measured CS lies between the CV and the EV measures (CV $\leq$CS $\leq$ EV) for the price-reduction case (Cherchi et al., 2004). The CV is always less than the CS. In addition, the resulting change in demand for transport (X) can be decomposed into a substitution effect ($X_3 - X_1$, from one good to the other) and an income effect ($X_2 - X_3$, more or less purchasing power for all goods because of an expansion or contraction of the budget) (Jong et al., 2007; Laird, 2009).

The CV is how much money we have to pay for the consumer in order to return to the original utility after the change of price has occurred (Hicks, 1942; Jong et al., 2005). On the other hand, the EV is how much money the consumer should give up before the change of price to prevent the price change. That is, CV is the minimum amount of additional money in income we would be likely to pay to reach its initial utility after the change of price whereas the EV is the minimum amount of money that is equivalent to the loss of income as the result of the price increase. In this sense, the EV can be seen as an *ex-ante* approach (based on the level of utility after the change) to cost-benefit analysis, whereas the CV an *ex post* approach (based on the level of utility before the change) (Hau, 1986). In general, the CV is considered a defined numerical indicator of welfare improvement.

The validity of the CS measure is related to the potential error involved in using it as an approximation for the income variation concepts. Therefore, the validity depends on the size of the income effect. In general, the measurement of the welfare change used to be measured by estimating the CV, to identify a winner and a loser under the change of price or policy intervention.

8.3. Application of Equity Assessment

8.3.1. Calculation method of consumer welfare

In order to estimate welfare change before and after the implementation of MSP under the assumption that the income effects are small enough to ignore, the utility function of travel mode choice can be utilized (Jara-Díaz and Videla, 1989). The key assumption that there is no income effect implies that the discrete choice probabilities are independent of the consumer's income. If income does not enter the utility function of travel mode choice, the specification of income results in zero income effects for all choice alternatives (Hau, 1983, 1986, 1987; Jong et al., 2007). That is, if the marginal utility of income is constant, there will be zero income effect. Therefore, due to the zero income effect, Hicksian welfare measures, such as the CV and the EV, coincide with the traditional MCS (Amador et al., 2005; Jara-Díaz and Videla, 1990). In the absence of income effects, CV equals EV, and CS (CV = CS = EV) (Hellström and Nordström, 2012). In addition, since logit models were developed, assessing consumer benefits based on random utility theory can be applied in this research. The welfare effect of an MSP can be measured as the change in the CS that results from a change of MSP (Alston and Larso, 1993; Jong et al., 2006). Small and Rosen (1981) show how marginal utility of income can be obtained from the coefficient of the cost variable in discrete choice models (Rodier et al., 1998). Through Small and Rosen (1981)'s formula, the CV can be calculated as follows (Small and Rosen, 1981; Rodier and Johnston, 1998; Boxall et al., 1996; Hanemann, 1982; Yai et al., 1997):

$$\mathrm{CV} = \Delta e_i = -\left(\frac{1}{\lambda_i}\right)\times\left[\mathrm{In}\sum_{k=1}^{2} e^{V_i^1} - \mathrm{In}\sum_{k=1}^{2} e^{V_i^0}\right] = \left(\frac{1}{\lambda_i}\right)\times\left[\mathrm{In}\sum_{k=1}^{2} e^{V_i^0} - \mathrm{In}\sum_{k=1}^{2} e^{V_i^1}\right] \qquad (8\text{-}1)$$

where 1: after the implementation of MSP *j* (= with MSP *j*, the final point)

0: before the implementation of MSP *j* (= without MSP *j*, the initial point)

λ_i: the individual's marginal utility of income

$\frac{1}{\lambda_i}$: the inverse of the individual's marginal utility of income

V_i: individual's indirect utility

V_i^0: individual's indirect utility of the choice of travel mode *k* before the implementation of MSP *j* (i.e. without MSP *j* intervention)

V_i^1: individual's indirect utility of the choice of travel mode *k* after the implementation of MSP *j* (i.e. with MSP *j* intervention)

$[\mathrm{In}\sum_{k=1}^{2} e^{V_i^1} - \mathrm{In}\sum_{k=1}^{2} e^{V_i^0}]$: the difference of each value of internal functions which can be estimative in the indirect utility

j : implementation of MSP (alternative-specific attribute)

K: travel mode (1: car, 2: PT)

The indirect utility function and the expenditure function can be identified with only mode choice data (Hau, 1986). The difference in expenditure functions, evaluated at the original utility and the final utility levels, yields the Hicksian welfare measures. The standard derivation of CV in the logit discrete choice formulation can evaluate the difference between the expected utilities with and without MSP. The CV can be assessed by income level using the variation of the marginal utility of income (Boxall et al., 1996). The expected CS in a logit model is simply the log of the denominator of the choice probability, divided by the marginal utility of income (Jong et al., 2005). In this research, the square brackets in **Equation 8-1** pertain to the expectation that an individual can gain the maximum utility obtained by the sum of car use and PT use. In addition, the CV can be converted into monetary values through these variations of expected maximum utility multiplied by the inverse of the marginal utility of income.

8.3.2. Calculation of the marginal utility of income

Although the researcher does not observe the indifference curve (U_i) in reality, the researcher can observe the deterministic part of the utility of travel mode (V_i) and know the distribution of utility. The CS pertaining to a set of choices can take a form that is easy to calculate. Because portions of the utility V_i that are common to all alternatives cannot be estimated from the choice model, λ cannot be estimated directly. λ can be determined from Roy's Identity (Small, 1992):

$$\lambda_i = \frac{\partial \mathrm{V}_i}{\partial \mathrm{Y}_i} = -\frac{1}{x_k} \cdot \frac{\partial \mathrm{V}_i}{\partial \mathrm{COST}_i} \tag{8-2}$$

where λ_i : the individual's marginal utility of income, the indirect utility function V_i was differentiated by the change of commuting cost variable in the mode choice model [a positive scale parameter will be estimated (SPECTRUM, 2005, p 43)]

$\frac{1}{\lambda_i}$: the inverse of the individual's marginal utility of income

COST_i : commuting cost of individual *i*

V_i : individual's indirect utility of the choice of travel mode

Y_i : income of individual *i*

x_k: individual's consumption of travel mode *k* conditional on choosing it among the discrete alternatives.

The change in indirect utility can be converted to unit of money by the factor $1/\lambda_i$, or the inverse of the individual's marginal utility of income. Meanwhile, Rodier et al. (1998) indicates that λ_i can be provided by the coefficient of the cost variable in the mode choice equations. This is based on an interpretation that the coefficient on the MSP attribute in the logit equation is equal to the marginal utility of income (Hanley et al., 1998). In this research, the coefficients of each MSP attribute are used as λ_i. In addition, the coefficients of MSP variables segmented by each income group are inversely proportional to income (Layard et al., 2008).

8.3.3. Classification of income group

To get the CV for each income category *h*, the commuter's households can be segmented into several income groups. In general, income groups can be divided into three groups (i.e. high-income, middle-income, or low-income group). In this research, although the income level is relatively higher than the average income level of Korea, the relative criterion of income classification can be used. This is mainly because this research focuses on the calculation of welfare effect of MSP. Due to the objective of the survey focusing on the modal shift from car to PT, it is inevitable that people in the high-income class tend to participate in this survey. That is, the rich tend to use a private car rather than the poor. In addition, since the Gangnam area is the wealthiest region in South Korea, the regional factor seems to affect the income distribution of respondents. **Table 8-3** shows total household income per month from survey samples.

Table 8-3. Total household income from all sources before tax per month from random samples

Level of household income	Samples	Percent	Valid percent	Classification
Up to 1,000,000 won (about £550)	1	0.1	0.1	**343** (44.9%)
1,000,001-2,000,000 won (about £551-£1,100)	16	2.1	2.1	
2,000,001-3,000,000 won (about £1,101-£1,650)	57	7.4	7.5	
3,000,001-4,000,000 won (about £1,651-£2,200)	137	17.9	17.9	
4,000,001-5,000,000 won (about £2,200-£2,750)	132	17.2	17.3	
5,000,001-6,000,000 won (about £2,751-£3,300)	125	16.3	16.4	**225** (29.4%)
6,000,001-7,000,000 won (about £3,301-£3,850)	100	13.0	13.1	
7,000,001-10,000,000 won (about £3851-£5,510)	141	18.4	18.5	**196** (25.7%)
More than 10000001 (over about £5,511)	55	7.2	7.2	
Total (valid data)	764	99.6	100	764
No response (missing data)	3	0.4		3
Total	767	100		767 (100%)

8.3.4. Compensating variation per person

An analysis of the incidence of cost and benefit can identify a winner and a loser. The assessment of who gains and who loses, and by how much, can influence the introduction of a new MSP.

The CV (Δe_{hj}) across income level can be multiplied by the number of commuters and then added up. Total CV can be obtained by summing the CV obtained from each income group (Lee, 2011b).

$$\Delta E_{hj} = \sum(\Delta e_{hj} \times N_h) \tag{8-3}$$

where *h*: income level (high, middle, low)

j : implementation of MSP (alternative-specific attribute)

ΔE_{hj}: total CV by income level

N_h: number of commuters by income level

Total CV (ΔE) can be defined as follows (Lee, 2011b):

$$\Delta E = \sum_{h=1}^{j} \Delta E_{hj} \tag{8-4}$$

The average Compensating Variation Per Person (CVPP) of three income groups when implementing MSP can be obtained (Lee, 2011b).

$$\Delta \overline{e_{hj}} = \frac{\Delta E_{hj}}{N_h} \tag{8-5}$$

where $\Delta \overline{e_{hj}}$: average CV by income level

N_h: number of total commuters by income level.

If the sign of $\Delta \overline{e_{hj}}$ is negative, the welfare change of MSP is improved. Conversely, if the sign of $\Delta \overline{e_{hj}}$ is positive, the welfare change of MSP is degraded. In general, the higher the absolute value of $\Delta \overline{e_{hj}}$, the greater the welfare change of MSP.

8.4. Result of Analysis

8.4.1. Basic application of model B0

Model B0, which is comprised of the main MSP coefficients without interaction terms, is selected as the basic model in the equity analysis. This is mainly because the simple specification and structure of model B0 can allow us to easily understand the distributional effect of each MSP. Since equity analysis focuses on the CV of each MSP, the research on interaction effects in the equity evaluation is not a necessity. In addition, since the results of equity evaluation in model B2 are almost the same as those of model B0, this research focuses on the equity assessment of model B0. However, the results of segmentation analysis of model B2 can be seen in **Reference Data 3** (**page 424**).

8.4.2. Application of the segmentation models using separate data of each income group

Table 8-4. The coefficients in segmentation models using separate data of each income group

Classification	Coefficient	Beta	Value	t-value	Goodness of fit
Low-income group	ASC	β_0	**-0.2100**	**-3.4367****	L(0) = - 5771.143 $L(\widehat{\beta})$= - 3304.137 ρ^2= 0.42743 Number of observations: 343
	PT commuting cost subsidy	β_1	**0.1719**	**10.7637****	
	Additional parking fee	β_2	**-0.2364**	**-14.7651****	
	Congestion charge	β_3	**-0.2400**	**-17.5728****	
Middle-income group	ASC	β_0	**0.2178**	**3.1420****	L(0) = - 3636.35 $L(\widehat{\beta})$= - 2521.688 ρ^2= 0.30651 Number of observations: 225
	PT commuting cost subsidy	β_1	**0.0556**	**3.9322****	
	Additional parking fee	β_2	**-0.2488**	**-14.0260****	
	Congestion charge	β_3	**-0.2932**	**-19.1048****	
High-income group	ASC	β_0	**0.4572**	**6.0776****	L(0) = - 2945.182 $L(\widehat{\beta})$= - 2322.89 ρ^2= 0.21129 Number of observations: 196
	PT commuting cost subsidy	β_1	**0.1399**	**7.8779****	
	Additional parking fee	β_2	**-0.2152**	**-11.9864****	
	Congestion charge	β_3	**-0.2236**	**-14.7539****	
Overall (low + middle + high income group)	ASC	β_0	0.0727	1.8804	L(0) = - 12405.26 $L(\widehat{\beta})$= - 8389.075 ρ^2= 0.32375 Number of observations: 764
	PT commuting cost subsidy	β_1	**0.1191**	**13.0699****	
	Additional parking fee	β_2	**-0.2287**	**-23.4739****	
	Congestion charge	β_3	**-0.2461**	**-29.5910****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Through the segmentation method using separate data of segmented income group, the CV of the segmented income group (low, middle, and high-income group) are measured. To this end, Small and Rosen (1981)'s formula is used as in **Equation 8-1**. As shown in **Table 8-4**, in the segmentation models using separate data of each segmented income group, the coefficients of MSP for the one income group are respectively different from those of the other income groups.

To understand the differences of equity impact across the income groups, the different λ_{hj}, which coincides with each income group, is used. That is, since the different coefficients of MSP for each income group are used, the values of the maximum utility difference between before and after MSP are also different. For example, in the calculation of utility of respondent *i* who belongs to the low income group, the coefficients of the low income group are applied into the utility function as in **Equation 8-6** and **Equation 8-7**.

$$V_{i,\,car} = -\,0.2100 + (-\,0.2364)\cdot Parking_j + (-\,0.2400)\cdot Congestion_j \quad (8\text{-}6)$$
$$V_{i,\,PT} = (0.1719)\cdot Subsidy_j \quad (8\text{-}7)$$

Before the implementation of an MSP (i.e. no policy intervention), the utility of the respondent *i* is calculated by the method of substitution as the below. In equity analysis, the total maximizing utility of respondent *i* is the sum of the utility of car use and the utility of PT use.

$$V_{i,\,car} = -\,0.2100 + (-\,0.2364)\cdot(0) + (-\,0.2400)\cdot(0) = -\,0.2100, \quad U_{i,\,car} = e^{-0.2100} = 0.810584 \quad (8\text{-}8)$$
$$V_{i,\,PT} = (0.1719)\cdot(0) = 0, \quad U_{i,\,PT} = e^{0} = 1 \quad (8\text{-}9)$$
$$U_i = U_{i,car} + U_{i,\,PT} = 0.810584 + 1 = \mathbf{1.810584} \quad (8\text{-}10)$$

As a result of the calculation, the total utility of the respondent *i* before the implementation of an MSP is 1.810584. In contrast, after the implementation of PT commuting cost subsidies (5,000 won), the utility of the respondent *i* is also calculated. In this case, the corresponding values will be five (5) since one scale means 1,000 won in this model.

$$V_{i,car} = -\,0.2100 + (-\,0.2364)\cdot(0) + (-\,0.2400)\cdot(0) = -\,0.2100, \quad U_{i,\,car} = e^{-0.2100} = 0.810584 \quad (8\text{-}11)$$
$$V_{i,\,PT} = (0.1719)\cdot(5) = 0.8595, \quad U_{i,\,PT} = e^{0.8595} = 2.361979 \quad (8\text{-}12)$$
$$U_i = U_{i,car} + U_{i,\,PT} = 0.810584 + 2.361979 = \mathbf{3.172564} \quad (8\text{-}13)$$

As shown in **Equation 8-13**, after the implementation of PT commuting cost subsidies at the level of 5,000 won, the total utility of the respondent *i* is 3.172564. In addition, the values of log sum (In (utility value)) and the difference values between the log sum before and after the MSP (i.e. In $\sum_{k=1}^{2} U_i^1$ – In $\sum_{k=1}^{2} U_i^0$) are calculated as follows:

$$\text{In} \sum_{k=1}^{2} U_i^0 = \text{In}\,(\mathbf{1.810584}) = 0.593649, \quad \text{In} \sum_{k=1}^{2} U_i^1 = \text{In}\,(\mathbf{3.172564}) = 1.154540,$$
$$\text{In} \sum_{k=1}^{2} U_i^1 - \text{In} \sum_{k=1}^{2} U_i^0 \rightarrow 1.154540 - 0.593649 = \mathbf{0.560891} \quad (8\text{-}14)$$

Finally, if the values of maximizing utility put into the CV formula in **Equation 8-1**, the CV would be obtained. In this case, λ_{hj} is 0.1719 since this is the coefficient of PT commuting cost subsidies

(β_1) (see **Table 8-4**). Therefore, the CV of PT commuting cost subsidies for the low income group is given by:

$$CV = -\left(\frac{1}{0.1719}\right) \times [\mathbf{0.560891}] = (-5.817336) \times \mathbf{0.560891} = \mathbf{-3.262889} \tag{8-15}$$

Table 8-5 shows the CVPP in every income group according to the change of policy intervention. Since the value of the CV means the change of money of MSP intervention (P_X), multipied by the variation of income (ΔY), the amount of policy intervention is always greater than the amount of the CV. Another cautious point is that the concept of the CV is the amount of compensation that is willing to pay for commuters in order to maintain the initial utility before the implementation of MSP. Therefore, if a positive CV result is drawn after the implementation of MSPs, the utility of the commuter is decreased and the commuter welfare is worse off. Conversely, if a negative CV result is derived, the utility of the commuter is increased and the commuter welfare is far greater.

Table 8-5. The CVPP of MSP in segmentation models using separate data of each income group (unit: won)

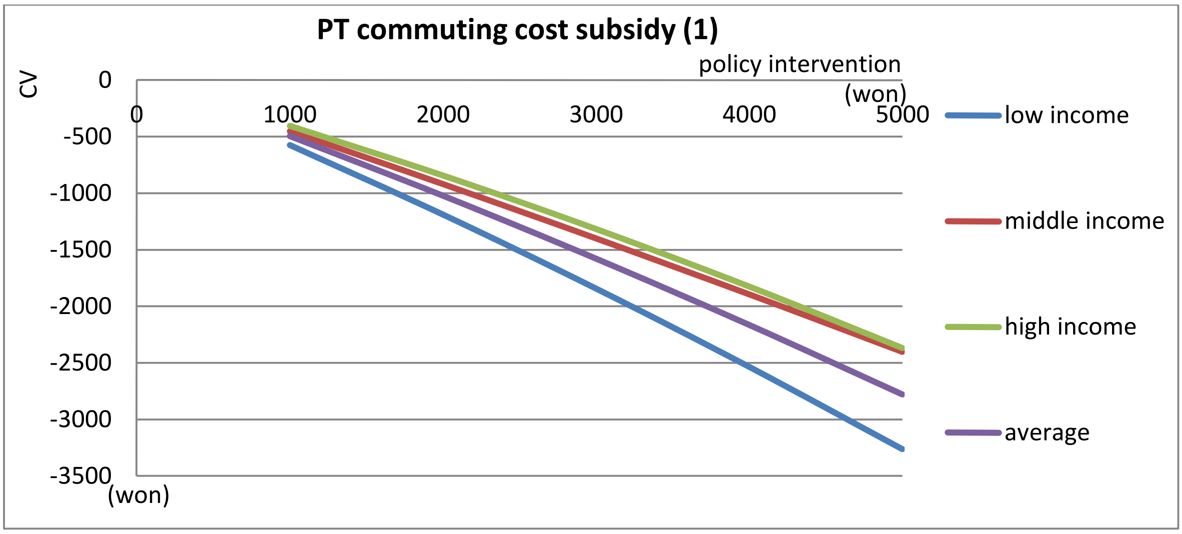
Type of MSP	Degree of policy intervention	Low income group	Middle income group	High income group	Average
Subsidy	1,000 won (=£0.56)	-573.41	-452.65	-404.42	-496.71
	2,000 won (=£1.11)	-1,188.22	-919.10	-842.92	-1,023.17
	3,000 won (=£1.67)	-1,842.83	-1,399.41	-1,316.09	-1,579.18
	4,000 won (=£2.22)	-2,535.19	-1,893.61	-1,824.20	-2,164.35
	5,000 won (=£2.78)	**-3,262.89**	-2,401.71	-2,367.16	**-2,778.11**
Parking	1,000 won (=£ 0.56)	418.77	523.30	586.44	489.60
	2,000 won (=£1.11)	781.40	984.58	1,119.96	922.49
	3,000 won (=£1.67)	1,091.40	1,385.01	1,599.79	1,300.38
	4,000 won (=£2.22)	1,353.27	1,727.50	2,026.39	1,626.24
	5,000 won (=£2.78)	1,572.10	2,016.41	2,401.42	**1,904.02**
Congestion	1,000 won (=£ 0.56)	418.34	517.76	585.42	487.43
	2,000 won (=£1.11)	779.73	962.59	1,115.80	913.95
	3,000 won (=£1.67)	1,087.81	1,336.77	1,590.39	1,281.70
	4,000 won (=£2.22)	1,347.26	1,645.30	2,009.84	1,594.36
	5,000 won (=£2.78)	1,563.34	1,895.07	2,376.06	**1,856.75**

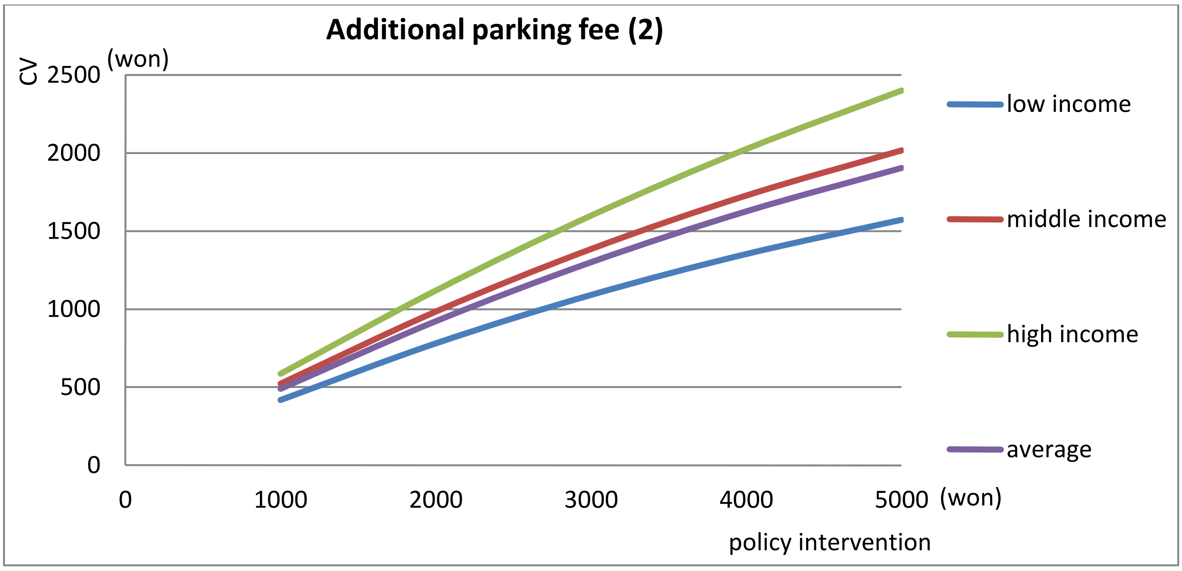
* Since number 1 means 1,000 won in the utility function, –3.262889 in **Equation 8-15** equals –3,262.89 won (Korean currency won).

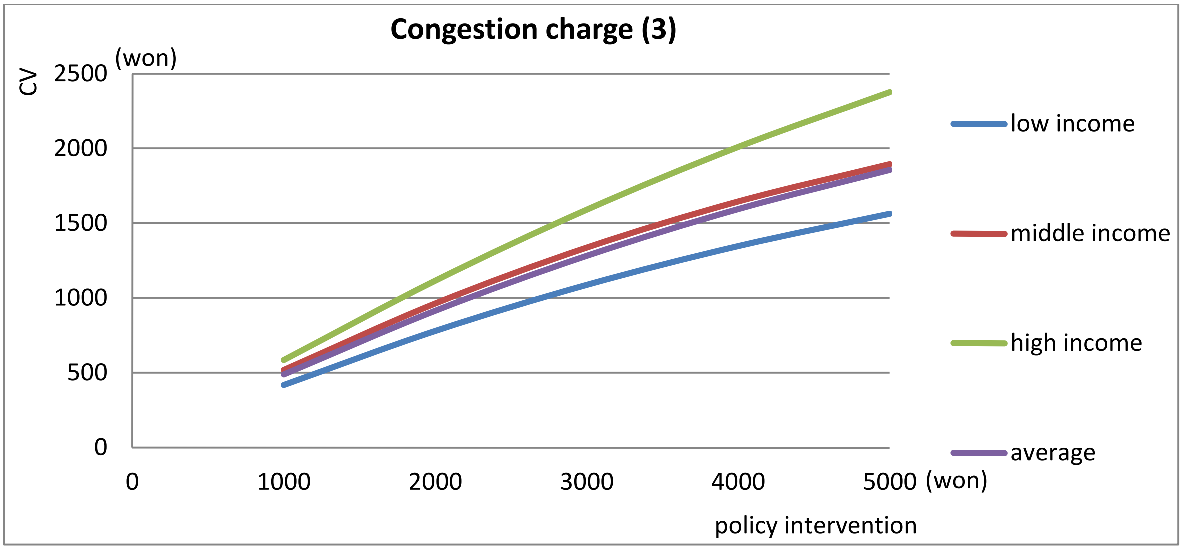
According to **Table 8-5**, in spite of the same monetary level of policy intervention for each income group, the income variation of each income group is different. For example, when a PT commuting cost subsidy is implemented at the level of 5,000 won (£ 2.78), the low income group gets a relatively higher CS (3,263 won, £ 1.81) than the high income group (2,367 won, £ 1.3). That is, the user benefit of the low-income group is about 38 % higher than the high-income group. In addition, in the case of congestion charges, the high-income group obtains higher consumer losses (2,376 won, £ 1.32) than the low-income group (1,563 won, £ 0.87). Meanwhile, when each MSP at the level of 5,000 won is implemented, the average CV value of PT commuting cost subsidies for PT users is **– 2,778 won** (£ 1.54), with additional parking fees, **1,904 won** (£ 1.06), and congestion charges **1,856 won** (£ 1.03). That is, the absolute average CV value of PT commuting cost subsidies is about 50% higher than that of congestion charges.

As shown in **Table 8-5** and **Figure 8-2**, when PT commuting cost subsidies is implemented, the lower income group obtains a larger CS compared to higher income group. That is, for PT commuting cost subsidies, the low-income group obtains higher benefits than the high-income group. This is mainly because the low-income group had a higher market share of PT than the high-income group. On the other hand, when additional parking fees or congestion charges are implemented, the low-income group gets smaller consumer losses than the high-income group. That is, for additional parking fees or congestion charges, the high-income group obtains higher consumer losses. This is mainly because the high-income group had a higher market share of car than the low-income group.

Figure 8-2. The CVPP of MSP in segmentation models using separate data of each income group







8.4.3. Application of a segmentation model using the income dummy variables

In the application of a segmentation model using dummy variables, the below utility function is used.

$V_{i,\,car} = \beta_0 + \beta_2 \cdot Parking_j + \beta_3 \cdot Congestion_j + \beta_{middle\ income} \cdot Dummy\ middle\ income$ (if the income of individual is between 5,000,000 won <£ 2,778> and 7,000,000 won<£ 3.889> taking the value1, and 0 otherwise) + $\beta_{high\ income} \cdot Dummy\ high\ income$ (if the income of individual is over 7,000,000 won taking the value1, and 0 otherwise) (8-16)

$V_{i,\,PT} = \beta_1 \cdot Subsidy_j$ (8-17)

Table 8-6 shows the coefficients of MSP in the segmentation model using income dummy variables. For every income group, the coefficients of MSP are the same in this model. However, due to the influence of different dummy variables (indicators), the value of the maximum utility of one income group is different from that of the other income groups.

Table 8-6. The coefficients of a segmentation model using the income dummy variables

Coefficient	Beta	Value	t-value	Goodness of fit
ASC	β_0	**-0.2808**	**- 6.2210****	L(0) = -12405.26 $L(\widehat{\beta})$= - 8171.184 ρ^2= 0.3413 Number of observations: 764
PT commute cost subsidy	β_1	**0.1211**	**13.0113****	
Additional parking fee	β_2	**-0.2334**	**-23.5898****	
Congestion charge	β_3	**-0.2514**	**-29.7452****	
Middle income (low income:0, middle income:1)	$\beta_{middle\ income}$	**0.5035**	**10.7775****	
High income (low income:0, high income:1)	$\beta_{high\ income}$	**0.8126**	**16.9600****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

The processes of calculation of the utility before and after the implementation of MSP and the CV are the same as those of the segmentation model using separate data, except for the way of dealing with dummy variables indicating whether the respondent corresponds to particular income group.

Table 8-7 shows the CVPP in every income group according to the change of policy intervention. As shown in **Figure 8-3** (1), when PT commuting cost subsidies is implemented, lower income group gets a larger CS compared to the higher income group. That is, as for PT commuting cost subsidies, the low-income group obtains greater user benefits than the high-income group. However, when additional parking fees or congestion charges are implemented, the low-income group receives smaller consumer losses than the high-income group.

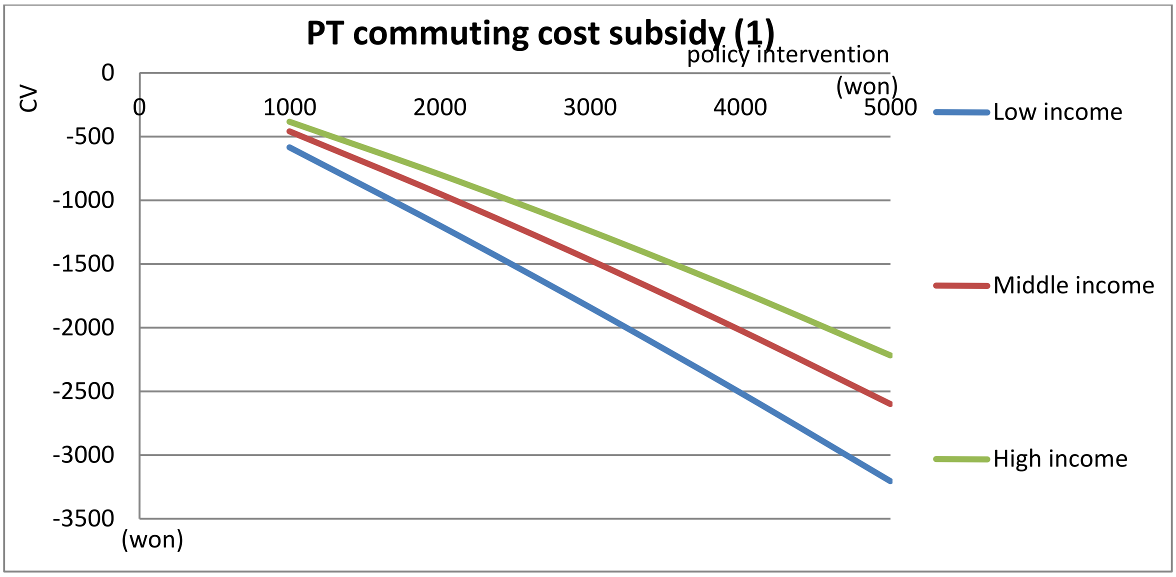
In comparison with **Table 8-5** and **Table 8-7** (**Figure 8-2** and **Figure 8-3**), these results are almost the same as those gained from segmentation models using separate data for the income groups. That is, although there are insignificant differences between the results calculated from the segmentation model using the income dummy variables and the ones estimated from the segmentation models using separate data for the income groups, the main results are almost the same.

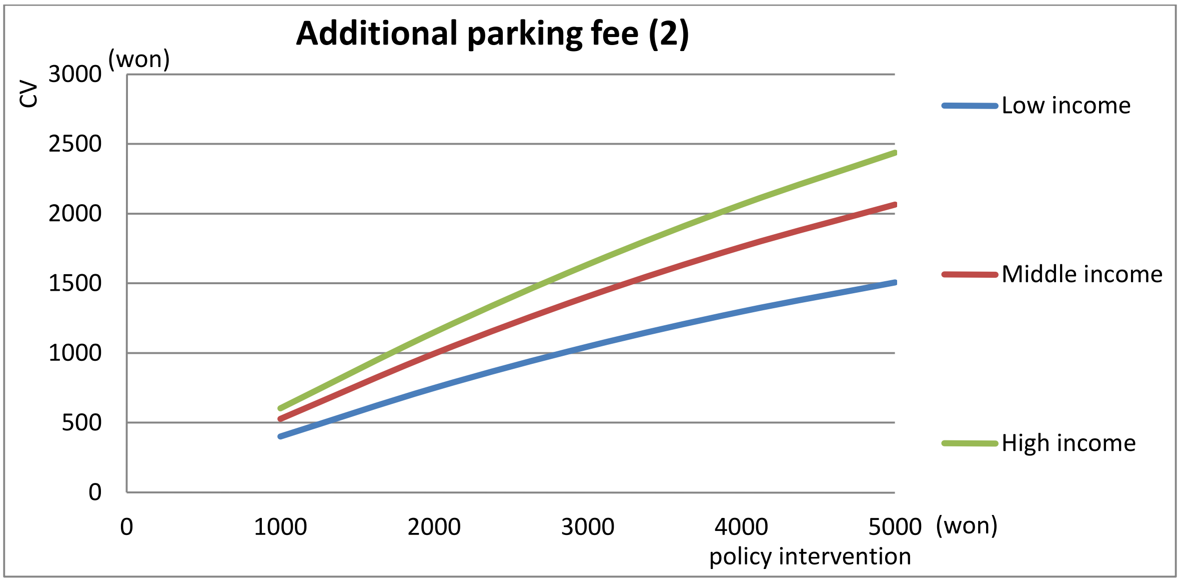
Table 8-7. The CVPP in income group in a segmentation model using the income dummy variables (unit: won)

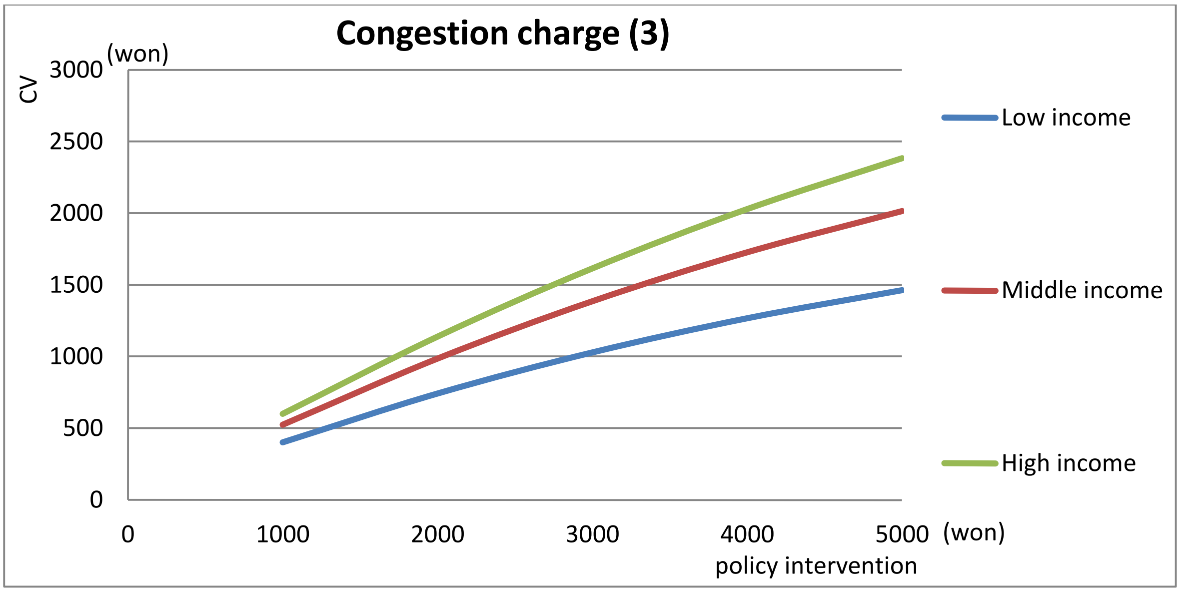
Type of MSP	Degree of policy intervention	Low-income group	Middle-income group	High-income group
Subsidy	1,000 won (=£0.56)	-584.49	-459.56	-384.35
	2,000 won (=£1.11)	-1,198.06	-949.31	-797.73
	3,000 won (=£1.67)	-1,839.90	-1,469.30	-1,240.73
	4,000 won (=£2.22)	-2,509.07	-2,019.40	-1,713.78
	5,000 won (=£2.78)	**-3,204.48**	-2,599.25	-2,217.06
Parking	1,000 won (=£0.56)	402.02	526.44	602.30
	2,000 won (=£1.11)	749.48	994.67	1,147.45
	3,000 won (=£1.67)	1,046.12	1,405.54	1,634.54
	4,000 won (=£2.22)	1,296.50	1,761.36	2,063.82
	5,000 won (=£2.78)	1,505.70	2,065.70	2,437.16
Congestion	1,000 won (=£0.56)	399.88	524.20	600.03
	2,000 won (=£1.11)	741.28	985.73	1,138.57
	3,000 won (=£1.67)	1,028.65	1,385.77	1,614.45
	4,000 won (=£2.22)	1,267.44	1,727.33	2,028.40
	5,000 won (=£2.78)	1,463.59	2,014.84	2,383.04

In addition, the CVPP values calculated by the Rule of Half convention (RoH) methods are attached at **Appendix 9**.

Figure 8-3. The CVPP of MSP in a segmentation model using dummy variables







8.4.4. Consideration of income level

Table 8-8 shows the monthly family income of urban workers. In addition, **Table 8-9** represents the level of monthly and daily income per income group.

Table 8-8. Household income distribution of urban workers in South Korea

Decile	Average monthly family income of an urban worker	Average monthly family income in three groups
average	₩4,616,619	₩4,616,619 (=£2,564.79)
1st	₩1,416,665	₩2,620,950 (=£1,456.83)
2nd	₩2,350,053	
3rd	₩2,935,525	
4th	₩3,481,820	
5th	₩3,969,407	₩4,696,934 (=£2,609.41)
6th	₩4,444,674	
7th	₩5,033,261	
8th	₩5,815,016	₩8,064,505 (=£4,480.28)
9th	₩6,858,076	
10th	₩9,842,669	

* Source: National statistics office data of South Korea, 2013.
* 1st + 2nd + 3rd + (1/3)*4th = 7,862,850*(1/3) = 2,620,950
(2/3)*4th + 5th + 6th + (2/3)*7th = 14,090,802*(1/3) = 4,696,934
(1/3)*7th+8th+9th+10th = 24,193,515*(1/3) = 8,064,505

Table 8-9. Level of monthly and daily income

Classification	Low-income group	Middle-income group	High-income group	Total (average)
Monthly income	₩2,620,950 (= £1,456.08)	₩4,696,934 (= £2,609.41)	₩8,064,505 (= £4,480.28)	₩4,616,619 (= £2,564.79)
daily income	₩124,807 (= £69.34)	₩223,664 (= £124.26)	₩384,024 (= £213.35)	₩219,839 (= £122.13)

* Daily income = Monthly income / 21 days (average working day per month in Korea)

In the evaluation of the distributional equity effects, the portion (π_h) of the CVPP to the average income of each income group can be utilized (Lee, 2011b).

$$\pi_h = \frac{\Delta\, \overline{e_{hJ}}}{\mathrm{AI}_h} \tag{8-18}$$

where π_h : the ratio of CVPP to the average income of each income level

AI_h : average income per income group

8.4.5. Whether a modal shift policy is a progressive policy or a regressive policy?

8.4.5.1. The concept and interpretation of ratio of compensating variation per person to the average income of segmented income group

The ratio (π_h) of the CVPP to the average income of each income group can be used to judge which group would become a winner or a loser. In general, according to the level of commuter's income, the burden and benefit felt by them are different. According to the sign of ratio (π_h), the distributional effect of MSP are arranged as follows.

First of all, suppose that the sign of π_h is positive. If the π_h value of the higher income group is higher tha the lower income group, the distributional equity (i.e. burdens) of MSP for the higher income group is relatively greater and the MSP will be progressive. The higher income group would pay a higher proportion of their income on MSP than the lower income group. Resultingly, a progressive policy has the desirable redistribution effect, and therefore helps the mitigation of income inequity. On the contrary, a regressive policy will aggravate the income equity. If the π_h of the lower income group is higher than the higher income group, the lower income group will suffer a higher ratio of welfare loss in the average income from MSP than the higher income group.

Second, suppose that the sign of π_h is negative. If the absolute value of π_h for the higher income group is higher than the lower income group, the distributional equity of MSP would be regressive. In this case, the higher income group would obtain a larger proportion of welfare benefit in their income than the lower income group. Conversely, if the absolute π_h value for the lower income group is higher than the higher income group, this MSP would be progressive. In this case, the lower income group would obtain a larger proportion of welfare benefit in their income from the implementation of MSP than the higher income group.

8.4.5.2. The ratio of compensating variation per person (CVPP) in segmentation models using separate data of each income group.

As indicated in **Table 8-10** and **Figure 8-4**, in the implementation of PT commuting cost subsidies at the level of 5,000 won, the absolute π_h value of the high income group ($|-0.62|$) is lower than the low income group ($|-2.61|$). Due to their negative signs of π_h, a PT commuting cost subsidy can be judged as a progressive policy. That is, the PT commuting cost subsidy can give a larger proportion of welfare benefit in their income to the low income group than the high income group.

Table 8-10. The π_h values of MSP in segmentation models using separate data of each income group

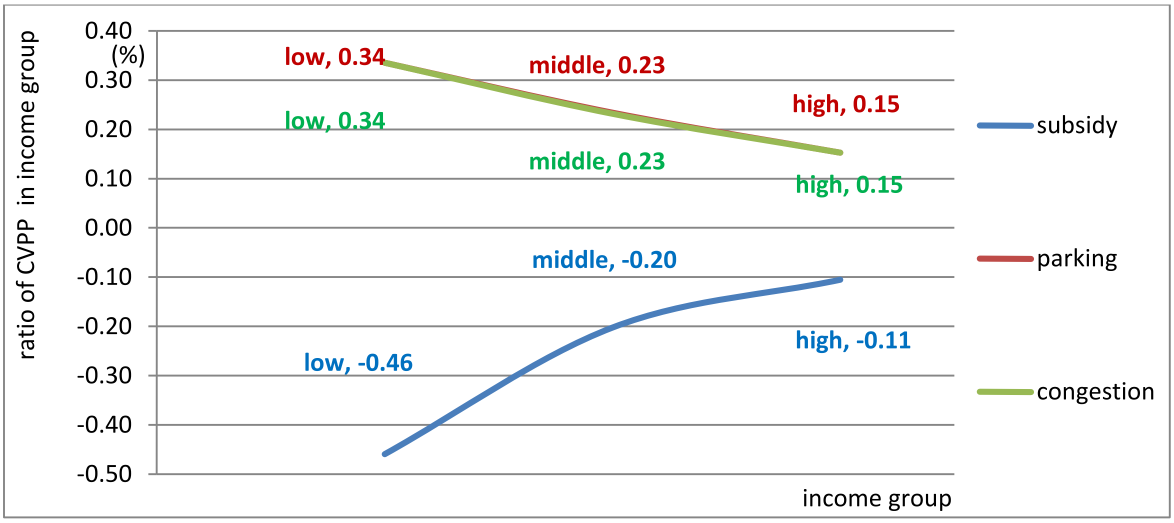
Policy intervention	Type of MSP	Low-income group	Middle-income group	High-income group	Total (Average)
₩1,000	Subsidy	-0.46	-0.20	-0.11	-0.23
	Parking	0.34	0.23	0.15	0.22
	Congestion	0.34	0.23	0.15	0.22
₩2,000	Subsidy	-0.95	-0.41	-0.22	-0.47
	Parking	0.63	0.44	0.29	0.42
	Congestion	0.62	0.43	0.29	0.42
₩3,000	Subsidy	-1.48	-0.63	-0.34	-0.72
	Parking	0.87	0.62	0.42	0.59
	Congestion	0.87	0.60	0.41	0.58
₩4,000	Subsidy	-2.03	-0.85	-0.48	-0.98
	Parking	1.08	0.77	0.53	0.74
	Congestion	1.08	0.74	0.52	0.73
₩5,000	Subsidy	**-2.61**	-1.07	**-0.62**	-1.26
	Parking	**1.26**	0.90	**0.63**	0.87
	Congestion	**1.25**	0.85	**0.62**	0.84

* Ratio of CVPP = CVPP / daily income (figures in **Table 8-5** / figures in **Table 8-9**) (unit: %)

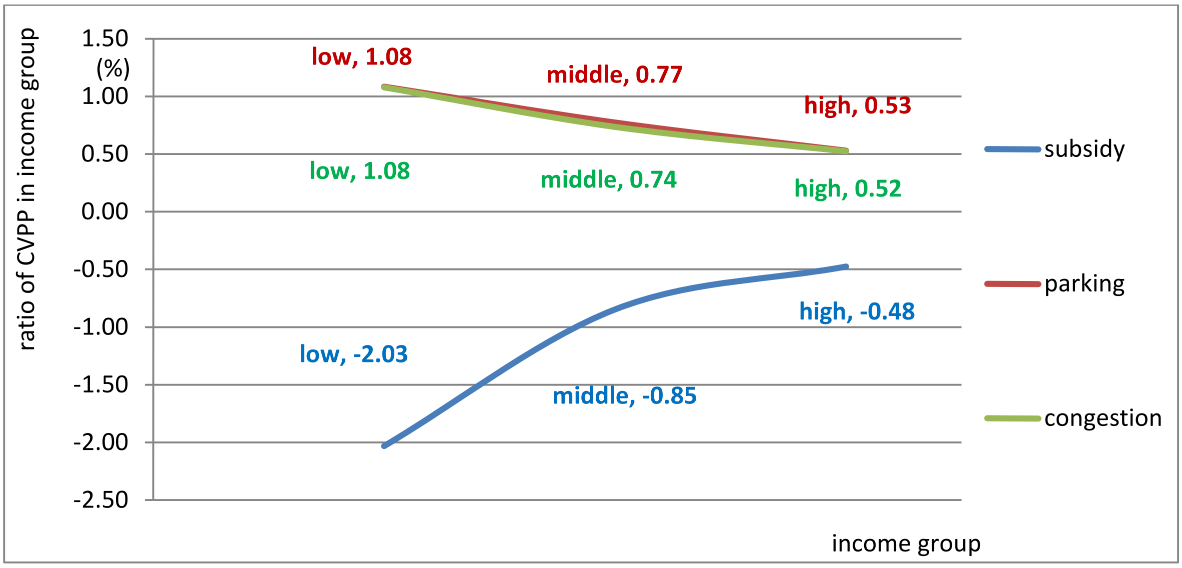
On the contrary, the signs of π_h for additional parking fees and congestion charges are positive. Since the π_h value of the high income group is smaller than of that the low income group, the two policies can be judged as regressive policies. As for additional parking fees, the π_h value of the high income group (|0.63|) is lower than the low income group (|1.26|). As for congestion charges, the π_h value for the high income group (|0.62|) is lower than the low income group (|1.25|). This implies that the high income group may pay a lower proportion of their income for MSP than the low income group. Thus, the low income group will face a higher proportion of welfare loss in their income from the two policies than the high income group. The introduction of the two policies would result in the aggravation of social equity since the burden of the poor is greater than the rich.

Figure 8-4. The π_h values of MSP in segmentation models using separate data of each income group

(1) Implementation of MSP at the level of 1,000 won



(2) Implementation of MSP at the level of 3,000 won



(3) Implementation of MSP at the level of 5,000 won

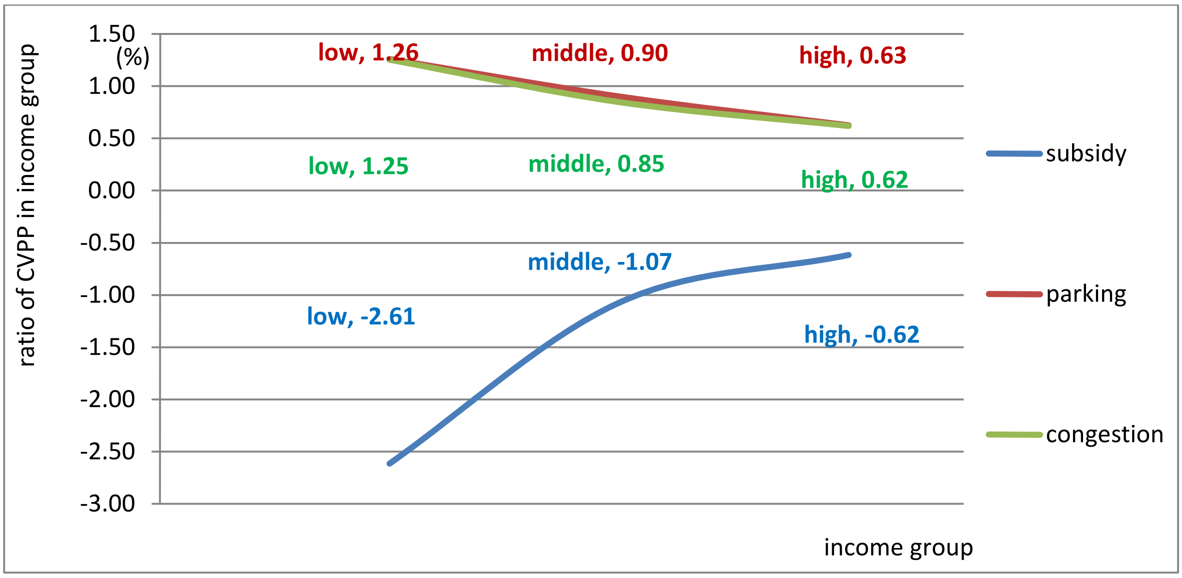
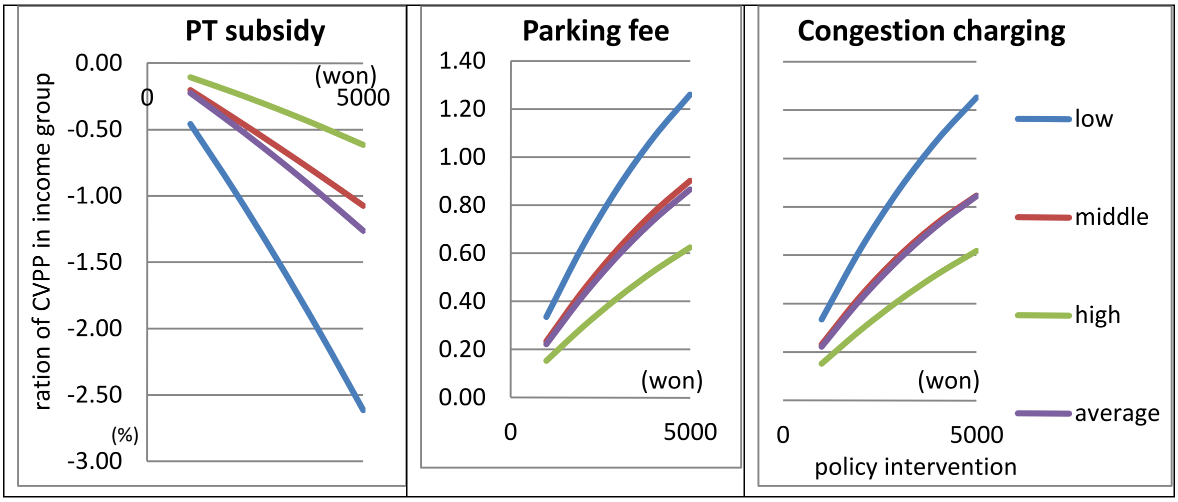


Table 8-10 is expressed as **Figure 8-5**. As policy intervention from 1,000 won to 5,000 won goes up, the absolute π_h values are increased regardless of the type of MSP (see **Figure 8-5**). In particular, the increase of the π_h for the low income group is greater than the other groups. It may suggest that the influence of the MSP on the low income group is bigger than the other groups.

As shown in **Table 8-10**, since all the π_h values are less than 5%, it can be concluded that the measurement of the CS in this research is a good approximation to the accurate CV measure.

Figure 8-5. The π_h values of MSP according to the monetary level of policy intervention



8.4.5.3. The ratio of compensating variation per person in a segmentation model of using dummy variables.

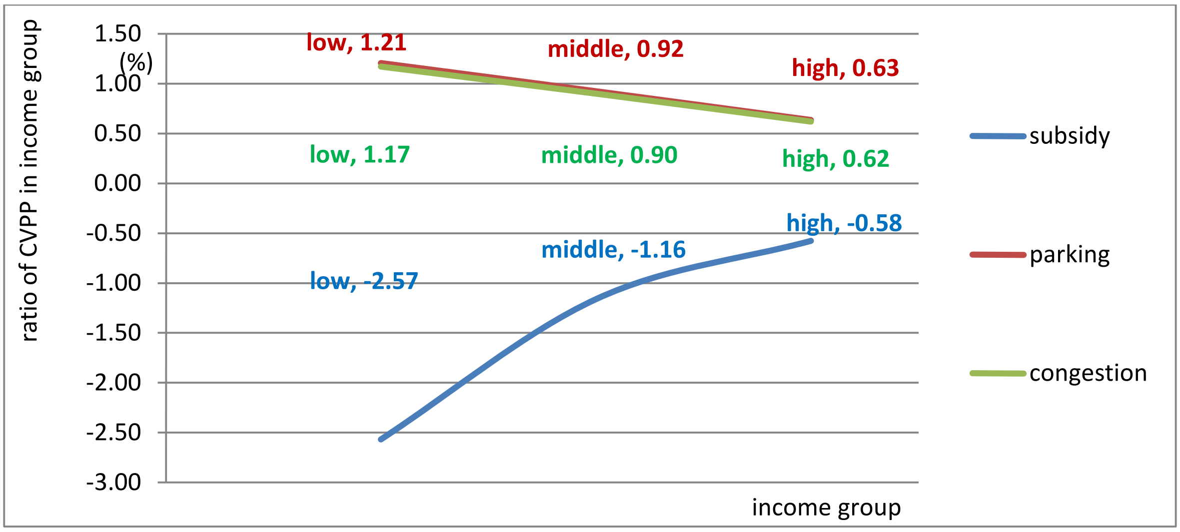
Table 8-11 and **Figure 8-6** show the π_h values of MSP in a segmentation model using dummy variables. If an MSP is implemented at the level of 5,000 won, the distributional equity effect of each income group in this model will be almost the same as that in segmentation models using separate data of each income group. That is, while a PT commuting cost subsidy is judged as a progressive policy, additional parking fees and congestion charges are judged as regressive policies.

Table 8-11. The π_h values of MSP in a segmentation model using dummy variables (unit: %)

Degree of policy intervention	Type of MSP	Low-income group	Middle-income group	High-income group
₩1,000	Subsidy	-0.47	-0.21	-0.10
	Parking	0.32	0.24	0.16
	Congestion	0.32	0.23	0.16
₩2,000	Subsidy	-0.96	-0.42	-0.21
	Parking	0.60	0.44	0.30
	Congestion	0.59	0.44	0.30
₩3,000	Subsidy	-1.47	-0.66	-0.32
	Parking	0.84	0.63	0.43
	Congestion	0.82	0.62	0.42
₩4,000	Subsidy	-2.01	-0.90	-0.45
	Parking	1.04	0.79	0.54
	Congestion	1.02	0.77	0.53
₩5,000	Subsidy	-2.57	-1.16	-0.58
	Parking	1.21	0.92	0.63
	Congestion	1.17	0.90	0.62

* Ratio of CVPP = CVPP / daily income (figures in **Table 8-7** / figures in **Table 8-9**)

Figure 8-6. The π_h values of 5,000 won MSP in a segmentation model using dummy variables



8.5. Equity Evaluation of Various Segmented Groups who Have Similar Characteristics

Equity evaluation for the various segmented groups sharing similar characteristics such as age, gender, region and so on, can be conducted in order to investigate the CS and determine whether equity impacts are fair or can be remedied (Givoni, 2013). The regional factor is selected as one example. In the application of a segmentation model, based on model B0, using a dummy variable, the utility function of respondent *i* is expressed as follows:

$V_{i,\,car} = \beta_0 + \beta_2 \cdot Parking_j + \beta_3 \cdot Congestion_j + \beta_{Dregion} \cdot Dummy\ region$ (if an individual lives outside of Seoul taking the value1, and 0 otherwise) (8-19)

$V_{i,\,PT} = \beta_1 \cdot Subsidy_j$ (8-20)

Table 8-12. The coefficients of MSP in a segmentation model using a dummy variable (region)

Coefficient	Beta	Value	t-value	Goodness of fit
ASC	β_0	0.0333	0.8153	L(0) = -12405.26
PT commuting cost subsidy	β_1	**0.1249**	**13.4701****	$L(\widehat{\beta})$= - 8327.89
Additional parking fee	β_2	**-0.2289**	**-23.4026****	ρ^2= 0.329
Congestion charge	β_3	**-0.2466**	**-29.5376****	Number of
Dummy region (living in Seoul:0, outside of Seoul:1)	β_{region}	**0.1297**	**3.2474****	observations: 674

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Table 8-12 shows the coefficients of MSP in a segmentation model using a regional dummy variable. These coefficients of MSP variables are used to estimate the CVPP. The calculation processes of the utility difference before and after the MSP and the CVPP are similar to the previous analysis (see **the section 8.4.**). **Table 8-13** shows the CVPP of the MSP in region groups according to the change of policy intervention.

Table 8-13. The CVPP of MSP in the region groups (unit: won)

Type of MSP	Degree of policy intervention	In Seoul	Outside of Seoul
Subsidy	1,000 won (=£ 0.56)	-507.28	-474.89
	2,000 won (=£1.11)	-1,045.71	-980.98
	3,000 won (=£1.67)	-1,614.98	-1,518.21
	4,000 won (=£2.22)	-2,214.56	-2,086.30
	5,000 won (=£2.78)	**-2,843.71**	**-2,684.73**
Parking	1,000 won (=£ 0.56)	479.75	512.12
	2,000 won (=£1.11)	902.93	967.20
	3,000 won (=£1.67)	1,271.50	1,366.40
	4,000 won (=£2.22)	1,588.61	1,712.22
	5,000 won (=£2.78)	**1,858.39**	**2,008.27**
Congestion	1,000 won (=£ 0.56)	477.54	509.91
	2,000 won (=£1.11)	894.28	958.43
	3,000 won (=£1.67)	1,252.64	1,347.10
	4,000 won (=£2.22)	1,556.54	1,679.08
	5,000 won (=£2.78)	**1,810.96**	**1,958.85**

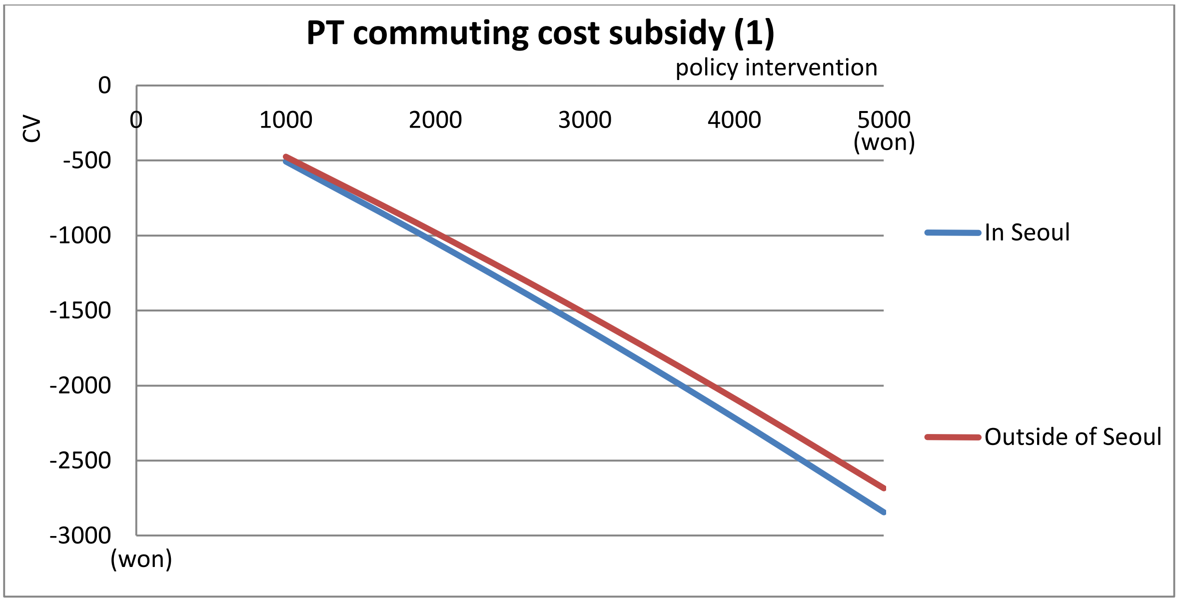
As shown in **Figure 8-7** (1), for PT commuting cost subsidies, people who live in Seoul gets a larger CS compared to people who live outside of Seoul. Since the CV is a minimum amount of compensation that is willing to pay for commuters in order to maintain the initial utility before implementation of MSP (Hicks, 1942; Jong et al., 2005), the lower graph (see the blue graph in **Figure 8-7 (1)**) implies gaining greater benefits from the implementation of the MSP. In spite of the same monetary level of policy intervention for each segmented group, the income variation of each regional group is different. For PT commuting cost subsidies, income variation (influence of this policy) to people who live in Seoul seems to be greater than people living outside of Seoul.

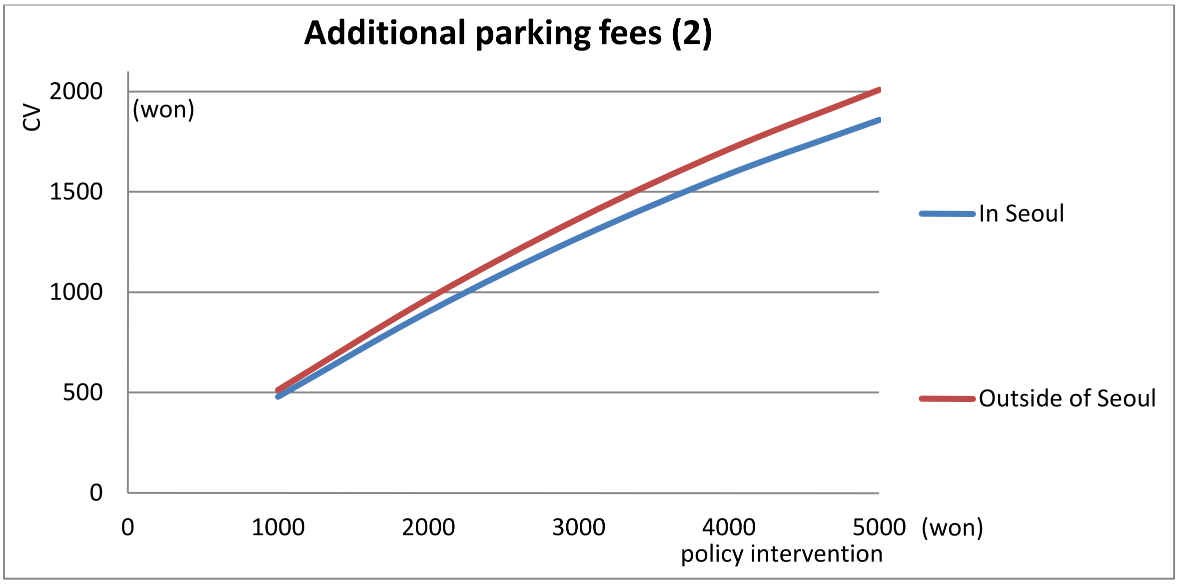
As can be seen in **Figure 7-1**, people who live in Seoul prefer the use of PT rather than people who live outside of Seoul in terms of the relative preferences of travel mode. In addition, as a result of calculation of CVPP of transport policy, the amount of welfare benefit for people who live in Seoul arising from the implementation of PT commuting cost subsidies is greater than people who live outside of Seoul (see **Figure 8-7 (1)**). These results are reasonable and acceptable.

Conversely, as shown in **Figure 8-7** (2) and (3), for additional parking fees and congestion charges, people who live in Seoul receive smaller consumer losses than people who live outside of Seoul. That is, for additional parking fees and congestion charges, income variation to people who live in Seoul is less than people who live outside of Seoul.

However, the amount of the CVPP for the segmented group is different from the ratio (π_h) of the CVPP to the average income of the segmented group. This ratio (π_h) seems to largely depend on the amount of income in the segmented group.

Figure 8-7. The CVPP of MSP for segmented regional groups





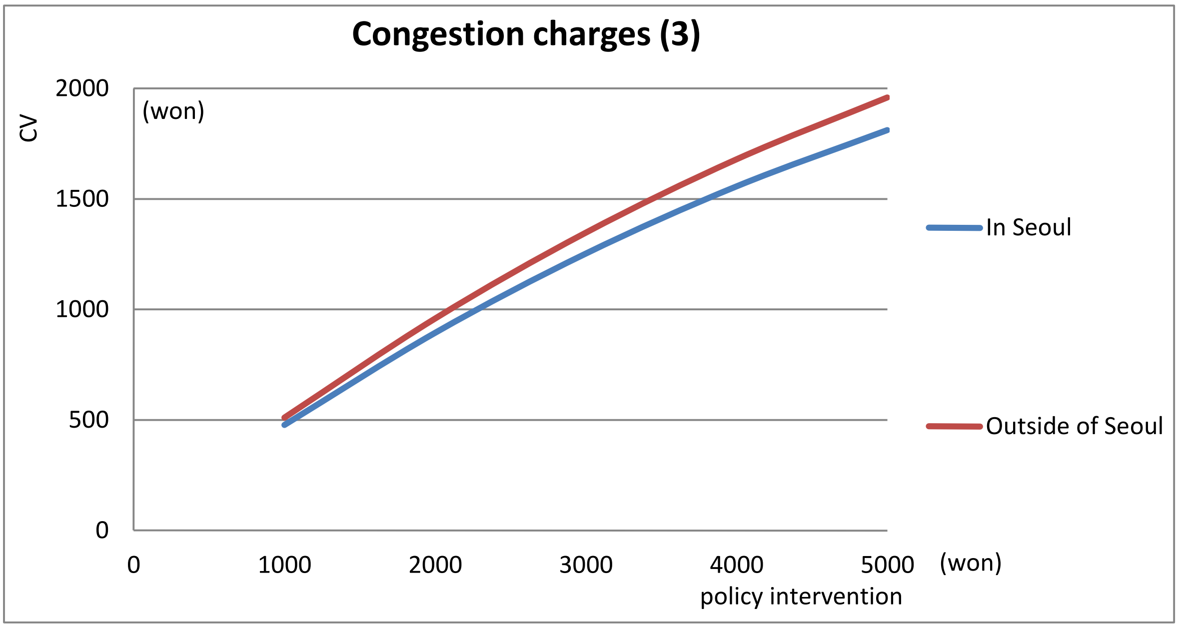


Table 8-14 and **Figure 8-8** show the π_h values of MSP for each segmented regional group in a segmentation model using a dummy variable. In addition, **Table 8-14** is expressed as **Figure 8-9** to easily compare the π_h of each segmented regional group according to the change of policy intervention. If a new MSP is implemented at the level of 5,000 won, the distributional equity of each segmented regional group will be changed. Since the data of daily income for each segmented regional group cannot be obtained, the average value of daily income of urban workers in South Korea (219,839 won, £122.13) is commonly applied in this analysis. In the implementation of a PT commuting cost subsidy, the absolute π_h value of MSP for people who live outside of Seoul (|– 1.22|) is lower than that of people who live in Seoul (|– 1.29|). Therefore, PT commuting cost subsidies can give a larger portion of welfare benefit in their income to people who live in Seoul than people who live outside of Seoul.

Table 8-14. The π_h values of MSP for each segmented region (unit: %)

Degree of policy intervention	Type of MSP	In Seoul	Outside of Seoul
₩1,000 (=£ 0.56)	Subsidy	-0.23	-0.22
	Parking	0.22	0.23
	Congestion	0.22	0.23
₩2,000 (=£ 1.11)	Subsidy	-0.48	-0.45
	Parking	0.41	0.44
	Congestion	0.41	0.44
₩3,000 (=£ 1.67)	Subsidy	-0.73	-0.69
	Parking	0.58	0.62
	Congestion	0.57	0.61
₩4,000 (=£ 2.22)	Subsidy	-1.01	-0.95
	Parking	0.72	0.78
	Congestion	0.71	0.76
₩5,000 (=£ 2.78)	Subsidy	**-1.29**	**-1.22**
	Parking	**0.85**	**0.91**
	Congestion	**0.82**	**0.89**

* Example of calculation: –1.29 = 100*(–2843.71)/219,839

On the contrary, as to additional parking fees, the π_h value of MSP for people who live in Seoul (|0.85|) is lower than people who live outside of Seoul (|0.91|). As for congestion charges, the π_h value of MSP for peopl living in Seoul (|0.82|) is also lower than people living outside of Seoul (|0.89|). This implies that people who live in Seoul might gain a lower proportion of consumer loss in their income on MSP than people who live outside of Seoul.

Figure 8-8. The π_h values of 5,000 won MSP for segmented regional groups

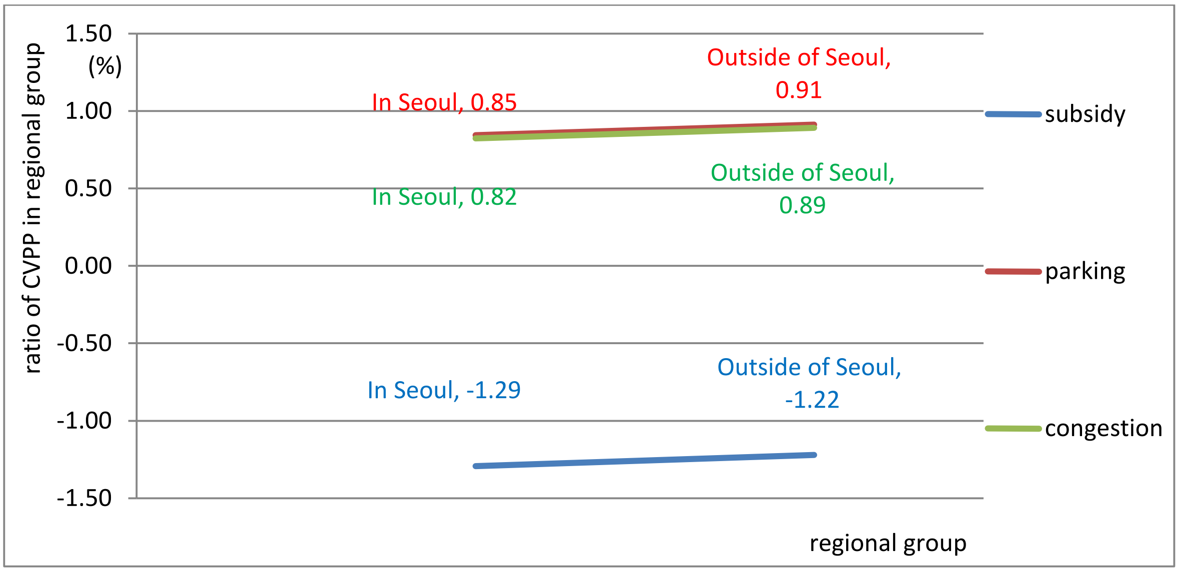


Figure 8-9 shows the change in the ratio (π_h) of the CVPP to the average income of each segmented regional group accroding to the level of MSP. As the level of policy intervention from 1,000 won to 5,000 won goes up, the absolute π_h value increases regardless of the types of MSP.

Figure 8-9. The π_h of the segmented regional group according to the change of policy intervention

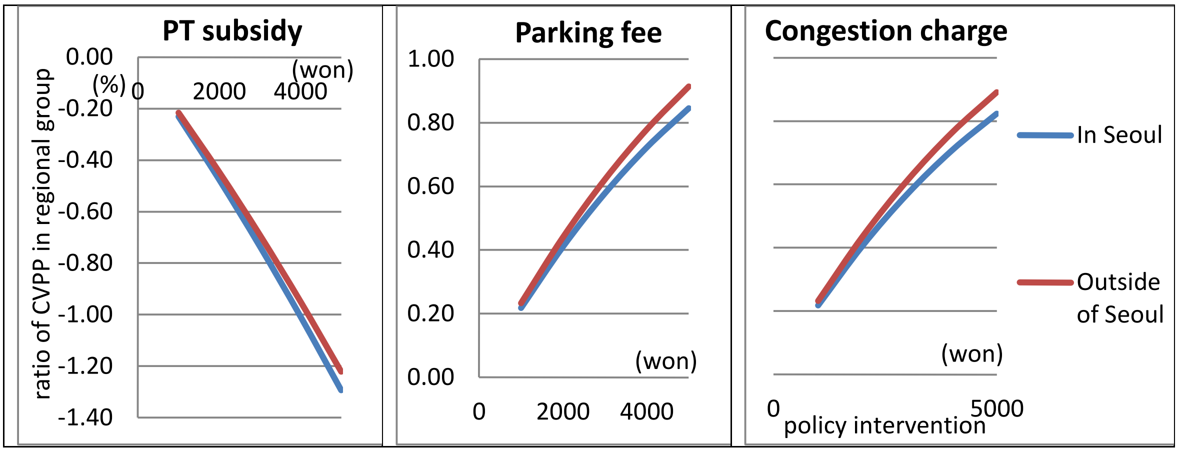
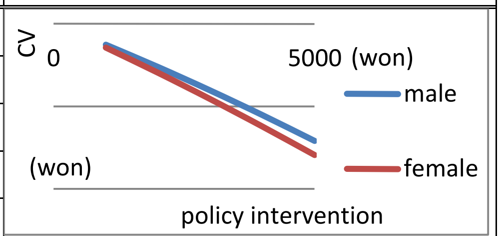
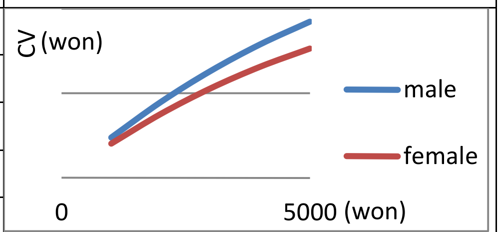
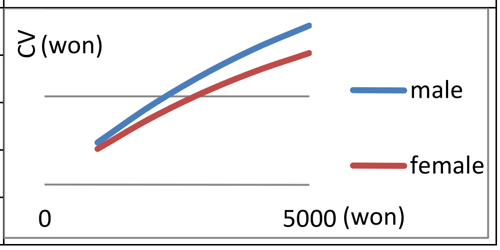


Table 8-15 represents the CVPP of MSP in gender. For example, since the absolute CVPP of PT commuting cost subsidies for the females is greater than the males, it can be interpreted that the females will get greater consumer benefits than the males. Conversely, for the additional parking fee, the females will get smaller consumer losses than the males. An interesting thing is that although the males prefer the use of PT rather than the females (see **Appendix Figure 7-1**), the amount of welfare benefit of the males from PT commuting cost subsidies is smaller than the females (see **Table 8-15**). Therefore, it can be inferred that the females are more sensitive to the level of the subsidy than the males. In other words, since the males would continue using a private car despite the increase of the level of the subsidy, the amount of welfare benefit of the males from the subsidy is smaller.

Table 8-15. The CVPP of MSP in gender

Type of MSP	Degree of policy intervention	Male	female	CVPP graphs of MSP with gender
Subsidy	₩1,000	-509	-581	
	₩2,000	-1,047	-1,190	
	₩3,000	-1,614	-1,827	
	₩4,000	-2,210	-2,491	
	₩5,000	-2,834	-3,180	
Parking	₩1,000	477	406	
	₩2,000	898	758	
	₩3,000	1,265	1,060	
	₩4,000	1,580	1,316	
	₩5,000	1,848	1,531	
Congestion	₩1,000	475	404	
	₩2,000	890	750	
	₩3,000	1,247	1,043	
	₩4,000	1,549	1,288	
	₩5,000	1,803	1,490	

In conclusion, the calculation of the CVPP allows to investigate whether any segmented group will gain greater welfare benefits or losses. In terms of equity, the equity effect of MSP can be measured according to a wide variety of segmented groups. The CVPPs of MSP in other segmented variables are attached to **Appendix 10**.

8.6. Summary

Marshall's basic idea is that when the proportion of income spent on a single good is small, the income effects are small. The small size of the income effect has been usually used to justify the MCS approximation to the Hicksian measure (Vives, 1987). Rosen and Small (1979) set forth that the CV could be calculated by using the estimates of conditional indirect utility function from logit models. Through Rosen and Small's welfare measure formula (see **Equation 8-1**), the welfare change of MSP are evaluated. Since the maximum utility before and after the MSP, as well as marginal utility of the MSP, are obtained using the utility functions, the CV are converted into monetary values.

Two segmentation methods both using separate data for the segmented income groups and using the income dummy variables are used. These methods offer almost the same results in terms of the amount of the CVs of segmented income group. First, the PT commuting cost subsidies would create welfare benefits whereas additional parking fees and congestion charges would make welfare losses. Second, as for the PT commuting cost subsidies, the low-income group would get a larger CS than the high-income group. For additional parking fees and congestion charges, the low-income group would get smaller consumer losses than the high-income group.

The ratio (π_h) of CVPP to the average income of each income group is used to judge which group would become a winner or a loser in term of the portion of CVPP in their total household income. For PT commuting cost subsidies, the absolute value of π_h for the high income group is lower than the low income group. Due to their negative signs of π_h, a PT commuting cost subsidy can be judged as a progressive policy. On the contrary, as for additional parking fees and congestion charges, the π_h value of the high income group is lower than the low income group. Due to their positive signs of π_h, additional parking fees and congestion charges are judged as regressive policies.

Additionally, as for various segmentation groups such as region, age, gender, and so on, equity evaluations have been carried out to investigate the amount of the CVPP. The result offers useful information on income variation of each segmented group.

Chapter 9. Development of Logit Models with Time and Cost Factors

9.1. Introduction

The purpose of this chapter is to develop models with travel time and cost factors. This chapter consists of three sections. Section 9.2 specifies models with commuting time and cost factors. Twelve models are developed according to several criteria. Section 9.3 represents the results of model estimation. The calculation process of the choice probability of a travel mode and the prediction of modal shift effects of MSPs are also presented. Section 9.4 presents the results of the MLMs with commuting time and cost variables.

9.2. Development of Utility Functions with Commuting Time and Cost Variables

9.2.1. Review of main data

Besides models with only alternative-specific variables, models with generic commuting time and cost variables are developed. Traditionally, it is widely recognized that the commuting time and commuting cost affect the choice of travel mode significantly. In transportation, commuting time and commuting cost are treated as some of the most important major independent variables. Therefore, the development of these types of models is needed to create good mode choice models. All the models with generic time and cost variables are based on a daily travel pattern to more delicately evaluate the variation of explanatory variables. Travel time and cost data are RP data as self-reported data from the survey. In addition, all the models with commuting time and commuting cost use both monetary unit (i.e. Korean currency won) and time unit (i.e. minute). **Table 9-1** shows the main data related to commuting time and commuting cost factors.

Table 9-1. Main data on commuting time and cost factors

Commuting cost	Detail contents (continuous variables)	Mean value
Car commuting cost (1)	(Adjusted car fuel cost*) × 2 + Present level of parking fee (once per day) + Present level of toll × 2 + other cost <e.g. rent cost> = 4,460.58 × 2 + 1,250.4 + 335.41 × 2 + 50.24 = 10,892.63 (from 619 observations) * Other average value : 10,960.03 (from 542 observations) = 4,502.47 × 2 + 1,298.89 + 314.35 × 2 + 27.49	**10,893 won (£6.05)**
Car commuting cost (2)	(Adjusted car fuel cost) × 2 + other cost = 4,460.58 × 2 + 50.24 = 8,971.4 (from 619 observations) (8,971.405493) * Other average value : 9,032.42 (from 542 observations) = 4,502.47 × 2 + 27.49	**8,971 won (£4.98)**
Car parking fee	Present level of parking fee 1,250.4 (once per day) (from 619 observations) * Other average values: 1,298.89 (from 542 observations)	1,250 won (£0.69)
Car toll	Present level of toll × 2 = 335.41 × 2 = 670.82 (from 619 observations) * Other average value : 314.35 (from 542 observations)	**671 won (£0.37)**
PT commuting cost	(PT fare + taxi fare + other cost) × 2 = (1.991.53 + 181.56 + 37.67) × 2 = 2,210.76692 × 2 = 4,421.53 (from 678 observations) (4,421.53392) * Other average value : 4,526.94 (from 542 observations) = (2,022.16 + 199.54 + 41.77) × 2 = 2,263.47 × 2	**4,422 won (£2.46)**
Car commuting cost – PT commuting cost (one way)	Commuting cost of car usage for one way – commuting cost of PT for one way = {(Adjusted car fuel cost)+ Present level of parking fee+ Present level of toll + other cost} – {(PT fare + taxi fare + other cost)} = 6,096.64 (from 619 observations) – 2,210.77 (from 678 observations) = 3,863.77 (from 546 observations) ★ Not 3,885.87 (because this value does not reflect the difference from overlapping part of the two components) * Other average value : 3,879.73 (from 542 observations) = 6,143.20 – 2,263.47	3,864 won (£2.15)
Car commuting cost (2) – PT commuting cost (round trip per one day)	{(Adjusted car fuel cost) × 2 + Present level of parking fee(once per day) + Present level of toll × 2 + other cost} – {(PT fare + taxi fare + other cost) × 2} = 10,892.63 – 4,421.53 = 6,410.87 (from 546 observations) (6,410.868132) ★ Not 6471.1 (because this value does not reflect the difference from overlapping part of the two components) * Other average value : 6,433.09 (from 542 observations) = 10,960.03 – 4,526.94	**6,411 won (£3.56)**
Car commuting cost (1) – PT commuting cost (one way)	{(Adjusted car fuel cost) + other cost} × 2 – {(PT fare + taxi fare + other cost)} × 2 = 8,971.4(from 619 observations) – 4,421.53 (from 678 observations) = 4,497.39 (from 546 observations) (4,497.388278) ★ Not 4,549.88 (because this value does not reflect the difference from overlapping part of the two components)	**4,497 won (£2.49)**

Commuting time	Detail contents (continuous variables)	Mean value
Car commuting time	Total travel time × 2 = 46.24 × 2 = 92.48 (from 666 observations) (92.48498498) * Other average value : 93.33 (from 542 observations) = 46.66 × 2	**92.48 minutes**
PT commuting time	Total travel time × 2 = 60.25 × 2 = 120.5 (from 695 observations) (120.494964) * Other average value : 122.54 (from 542 observations) = 61.27 × 2	**120.5 minutes**
(Car – PT) commuting time	92.48 minutes (from 666 observations) – 120.5 minutes (from 695 observations) = – 28.58 minutes (from 598 observations) (– 28.57692308) ★ Not – 28.2 minutes (because this value does not reflect the difference from overlapping part of the two components) * Other average value : – 29.2 (from 542 observations) = – 14.6 × 2	**– 28.58 minutes**
Reduced commuting time of congestion charging	1 level (10% reduction of total travel time) = 9.248 {Total travel time × 1 (=92.48)} × 1/10 = 9.248 2 level (20% reduction of total travel time) = 18.496 {Total travel time × 2 (=92.48)} × 2/10 = 18.496	1 level: 9.25minutes 2 level: 18.49minutes

* Adjusted car fuel cost: The values of car fuel cost were adjusted within 50%~150% of standard values [distance (km) from home to work × 200 won (= £0.11) per 1 km]. Since many over-estimations or under-estimations seemed to exist in the calculation of car fuel cost (317 out of 619), the adjustments have been carried out. After that, the mean value was changed 6,049.22 won into 4,460.58 won. For reference, the average price of petrol in South Korea was 1,900 won (£1.05) per 1 litter as of June, 2013. In addition, the range of car mileage was from 8 to 24 (km/ℓ).
* Travel cost and time are calculated on a basis of a daily travel pattern.

9.2.2. Development of utility function with commuting time and cost

9.2.2.1. Specification of commuting time and cost variables

In general, the only differences of commuting time between car and PT cannot reflect the recognition of the difference between respondents who take a long travel time and those who take a short travel time. That is, since an independent 'Car Commuting Time' variable can significantly influence the choice decision on travel mode, a coefficient associated with the 'Car Commuting Time' variable should be included in the utility function in order to estimate good models. The consideration of the 'PT Commuting Cost' variable should be subsumed in the specification of models due to the same reasons as well. All in all, these models include 'Car Commuting Time', 'PT Commuting Cost', '(PT – Car) Commuting Time', and '(Car – PT) Commuting Cost' variable.

The basic utility functions with commuting time and cost variables have four variables related to commuting time and cost variables. Since the car commuting time tends generally to be shorter than the PT commuting time (Hine and Scott, 2000) and then can be regarded as a rising factor for the utility of a car, the inclusion of this variable into the utility function of car use can be acceptable. In addition, it allows to be a positive value since the positive value makes easy and consistent handling in the process of data. Instead, the '(PT – Car) Commuting Time$_i$' variable, which can be regarded as a kind of excess time (positive value) occurring from the use of PT, can be counted in the utility function of PT in order to balance the utility functions of the car. It also allows to be a positive value. Meanwhile, because PT commuting cost tends to be cheaper than car commuting cost, it is acceptable that the 'PT Commuting Cost$_i$' is taken account of the inclusion of the utility function of PT. On the other hand, the '(Car – PT) Commuting Cost$_i$', which is regarded as a kind of excess cost occurring from the use of cars, is reckoned in the utility function of the car. All the models with the commuting time and cost factors (i.e. models D, E, F and G) have the same structures in terms of having four variables. However, whether the commuting cost variable and the commuting time variable attribute to the utility function of the car or the utility function of PT is not a crucial part of understanding the utility functions because the arrangement of time and cost variables tends to change just the sign of the variable. All in all, this study reviews on the differences in additional commuting time and additional commuting cost of travel mode aside from the magnitude of the minimum commuting time and the minimum commuting cost which is commonly taken during the commuting period. In addition, since the travel distance is directly connected to the commuting time, this factor (i.e. travel distance) is excluded in the model specification.

9.2.2.2. Type of models with commuting time and cost variables

Table 9-2 shows the criteria of models having commuting cost and commuting time factors. In the classification of models with commuting time and cost variables, according to whether the current toll and current parking fee are included in the 'alternative-specific variables' or the '(Car – PT) Commuting Cost' variable, models can be classified as (1) 'models D and models E' and (2) 'models F and models G'. That is, models D and models E are models with the reflection of the 'current tolls' and 'current parking fees' into the '(Car – PT) Commuting Cost' variable. Conversely, models F and models G are models with the reflection of the 'current tolls' and 'current parking fees' into the 'alternative-specific variables (MSP)'. Another criterion is whether the reduced commuting time effect derived from the implementation of congestion charges is reflected in a model or not. Models D and models F do not reflect the reduced travel time values of congestion charges in their utility function whereas models E and models G reflect these values into the '(Car – PT) Commuting Cost$_i$' variable in their utility function. In addition, in terms of interaction terms, models 0 (i.e. model D0, model E0, model F0 and model G0) are models without interaction terms whereas both models 1 and models 2 are models with interaction terms. In particular, while models 1 are models with interaction terms including statistically insignificant coefficients, models 2 are models with interaction terms comprising only statistically significant coefficients.

Table 9-2. Criteria for models with commuting cost and time factors

<table>
<tr><td colspan="2">Type of model</td><td colspan="2">Models D and models F</td><td colspan="2">Models E and models G</td></tr>
<tr><td colspan="2" rowspan="2">Whether put 'current parking fee' and 'current toll' into 'alternative-specific variable (MSP)' or 'Cost (Car – PT) variable'?</td><td colspan="4"></td></tr>
<tr><td>Cost (Car – PT) variable</td><td>Alternative-specific variable</td><td>Cost (Car – PT) variable</td><td>Alternative-specific variable</td></tr>
<tr><td>0</td><td>Model without interaction Terms</td><td>D0</td><td>F0</td><td>E0</td><td>G0</td></tr>
<tr><td>1</td><td>Model with interaction terms including statistically insignificant</td><td>D1</td><td>F1</td><td>E1</td><td>G1</td></tr>
<tr><td>2</td><td>Model with interaction terms comprised of only statistically significant</td><td>D2</td><td>F2</td><td>E2</td><td>G2</td></tr>
<tr><td colspan="2">· Whether reduced commuting time effect come from the implementation of congestion charging is included in the utility function or not</td><td colspan="2">· Alternative-specific variables + Time (Car) variable, Time (PT – Car) variable, Cost (PT) variable, Cost (Car – PT) variable</td><td colspan="2">· Alternative-specific variables + Time (Car) variable, Time (PT – Car) Variable［reflects reduced time value time derived from the implementation of congestion charges］, Cost (PT) variable, Cost (Car – PT) variable</td></tr>
</table>

* Cost (Car – PT) variable: Since the car commuting cost is usually higher than the PT commuting cost, the value of the 'Cost (Car – PT) variable' will be a positive value. A positive value might be handy to use it. Therefore, the 'Cost (Car – PT)' term is used in the model specification.

* Time (PT – Car) variable: Since the PT commuting time is usually longer than the car commuting time, the value of the 'Time (PT – Car) variable' will be a positive value. A positive value might be handy to use it. Therefore, the 'Time (PT – Car)' term is used in the model specification.

Table 9-3 shows the utility function forms of models having commuting time and cost variables.

Table 9-3. The utility function forms of models having commuting time and cost variables

Model D0	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$(Car – PT) Commuting Cost$_i$ 〔= (Car – PT) Commuting Cost + current car parking fee + current car toll〕 + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j$
Model E0	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$\{(Car – PT) Commuting Cost$_i$ 〔= (Car – PT) Commuting Cost + current car parking fee + current car toll〕 – Reduced commuting time effect come from congestion charge policy$_{i,car}\cdot$(if level 1 = 0.1, if level 2 = 0.2)\} + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j$
Model D1	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$(Car – PT) Commuting Cost$_i$ 〔= (Car – PT) Commuting Cost + current car parking fee + current car toll〕 + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j$
Model E1	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$\{(Car – PT) Commuting Cost$_i$ 〔= (Car – PT) Commuting Cost + current car parking fee + current car toll〕 – Reduced commuting time effect come from congestion charge policy$_{i,car}\cdot$(if level 1 = 0.1, if level 2 = 0.2)\} + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j$
Common	$V_{i,\,PT} = \beta_5 \cdot$(PT – Car) Commuting Time$_i$ + $\beta_6 \cdot$PT Commuting Cost$_i$ + $\beta_1 \cdot Subsidy_j$
Model F0	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$(Car – PT) Commuting Cost$_i$ + $\beta_2 \cdot Park_j$ 〔= $Park_j$ + current car parking fee〕 + $\beta_3 \cdot Congestion_j$ 〔= $Congestion_j$ + current car toll〕
Model G0	$V_{i,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$\{(Car – PT) Commuting Cost$_i$ – Reduced commuting time effect come from congestion charge policy$_{i,car}\cdot$(if level 1 = 0.1, if level 2 = 0.2)\} + $\beta_2 \cdot Park_j$ 〔= $Park_j$ + current car parking fee〕 + $\beta_3 \cdot Congestion_j$ 〔= $Congestion_j$ + current car toll〕
Model F1	$V_{i,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$(Car – PT) Commuting Cost$_i$ + $\beta_2 \cdot Park_j$ 〔= $Park_j$ + current car parking fee〕 + $\beta_3 \cdot Congestion_j$ 〔= $Congestion_j$ + current car toll〕 + $\beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j$
Model G1	$V_{i,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$\{(Car – PT) Commuting Cost$_i$ – Reduced commuting time effect come from congestion charge policy$_{i,car}\cdot$(if level 1 = 0.1, if level 2 = 0.2)\} + $\beta_2 \cdot Park_j$ 〔= $Park_j$ + current car parking fee〕 + $\beta_3 \cdot Congestion_j$ 〔= $Congestion_j$ + current car toll〕 + $\beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j$
Common	$V_{i,\,PT} = \beta_5 \cdot$(PT – Car) Commuting Time$_i$ + $\beta_6 \cdot$PT Commuting Cost$_i$ + $\beta_1 \cdot Subsidy_j$

* Model D2, model E2, model F2 and model G2 can be developed as models with interaction terms including only statistically significant coefficients.

9.3. Estimation Results of Standard Logit Models with Commuting Time and Cost Factors

9.3.1. Review of the goodness of fit of models and coefficients

Table 9-4 shows the estimation results of the models with commuting time and cost factors. Although the number of explanatory variables is increased, the goodness of fit (ρ^2) in these models is sometimes superior [e.g. model C0 (0.278) < model E0 (0.298)] or sometimes inferior [e.g. model B0 (0.324) > model D0 (0.298)] to that of models with only 'alternative-specific variables'. It is assumed that missing values on the 'PT Commuting Time', 'Car Commuting Time', 'PT Commuting Cost', 'Car Commuting Cost', and current parking fees from the survey data seem to influence the likelihood values. However, since the ρ^2 values of models are higher than 0.2, these models can be considered as models with a good fit (Ortúzar and Willumsen, 2011).

In **Table 9-4**, the signs of the coefficients (β_4) involving 'Car Commuting Time' are negative. It suggests that there is a reverse relationship between the 'Car Commuting Time' variable and the utility of the car. In addition, the signs of the coefficients (β_7) involving the difference of commuting cost between the car and the PT are negative. It indicates that there is a reverse relationship between the '(Car – PT) Commuting Cost' variable and the utility of the car.

Meanwhile, the signs of the coefficients (β_5) related to the difference of commuting time between the car and the PT are negative. It suggests that there is a reverse relationship between the '(PT – Car) Commuting Time' variable and the utility of PT. In addition, the signs of the coefficients (β_6) involving the 'PT Commuting Cost' are also negative. It means that there is a reverse relationship between the 'PT Commuting Cost' variable and the utility of PT. The signs of the coefficients are acceptable since an increase of time or cost leads to a decrease of consumer's utility in general. As shown in **Table 9-4**, the magnitude of the coefficients related to commuting time and commuting cost (β_4, β_5, β_6, and β_7) in models D is almost the same as that of models E. In addition, these values of models F are almost the same as those of models G.

Table 9-4. Estimation results of models with commuting time and cost variables

Model	Coefficient	Beta	Value	t-value	Goodness of fit of model
Model D0	ASC	β_0	0.1263	1.7967	
	Time (Car)	$\boldsymbol{\beta_4}$	**-0.0023**	**-3.2112****	
	Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.0118**	**-17.5567****	L(0) = - 10015.28
	Cost (Car – PT)	$\boldsymbol{\beta_7}$	**-0.0108**	**-2.6872****	$L(\widehat{\beta})$= - 7028.173
	Cost (PT)	$\boldsymbol{\beta_6}$	**-0.0810**	**-9.2232****	ρ^2= 0.298
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.1821**	**17.7424****	Number of observations: 542
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.2549**	**-24.0966****	
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.2732**	**-30.2466****	

	ASC	β_0	0.1334	1.8101	
	Time (Car)	β_4	**-0.0024**	**-3.0184****	
	Time (PT – Car)	β_5	**-0.0119**	**-17.6173****	L(0) = - 10015.28
Model E0	**Cost (Car – PT)**	β_7	**-0.0113**	**-2.8065****	$L(\hat{\beta})$= - 7028.678
	Cost (PT)	β_6	**-0.0803**	**-9.1538****	ρ^2= 0.298
	PT commuting cost subsidy	β_1	**0.1820**	**17.7377****	Number of observations: 542
	Additional parking fee	β_2	**-0.2549**	**-24.0960****	
	Congestion charge	β_3	**-0.2802**	**-29.9904****	
	ASC	β_0	**-0.5312**	**-7.9280****	
	Time (Car)	β_4	-0.0005	-0.6364	
	Time (PT – Car)	β_5	**-0.0126**	**-18.1523****	L(0) = - 10015.28
Model F0	**Cost (Car – PT)**	β_7	**-0.0189**	**-3.1945****	$L(\hat{\beta})$= - 7370.593
	Cost (PT)	β_6	**-0.0949**	**-10.2152****	ρ^2= 0.264
	PT commuting cost subsidy	β_1	**0.1729**	**17.3381****	Number of observations: 542
	Additional parking fee	β_2	**-0.0669**	**-10.5364****	
	Congestion charge	β_3	**-0.2030**	**-25.9897****	
	ASC	β_0	**-0.5319**	**-7.8144****	
	Time (Car)	β_4	-0.0001	-0.0950	
	Time (PT – Car)	β_5	**-0.0118**	**-17.1433****	L(0) = - 10015.28
Model G0	**Cost (Car – PT)**	β_7	**-0.0223**	**-3.7851****	$L(\hat{\beta})$= - 7409.354
	Cost (PT)	β_6	**-0.0933**	**-10.0344****	ρ^2= 0.260
	PT commuting cost subsidy	β_1	**0.1716**	**17.2797****	Number of observations: 542
	Additional parking fee	β_2	**-0.0666**	**-10.5129****	
	Congestion charge	β_3	**-0.2304**	**-27.9892****	

	ASC	β_0	**0.5188**	**6.1903****	
	Time (Car)	β_4	**-0.0024**	**-3.2818****	
	Time (PT – Car)	β_5	**-0.0119**	**-17.6410****	
	Cost (Car – PT)	β_7	**-0.0108**	**-2.6661****	
	Cost (PT)	β_6	**-0.0813**	**-9.2605****	L(0) = - 10015.28
Model D1	**PT commuting cost subsidy**	β_1	**0.2984**	**14.4515****	$L(\hat{\beta})$= - 6981.754
	Additional parking fee	β_2	**-0.3803**	**-18.9020****	ρ^2= 0.303
	Congestion charge	β_3	**-0.3889**	**-22.2419****	Number of observations: 542
	Subsidy & Parking	β_{12}	**0.0293**	**4.5517****	
	Subsidy & Congestion	β_{13}	**0.0281**	**5.1165****	
	Parking & Congestion	β_{23}	**0.0349**	**6.0269****	
	Subsidy & Parking & Congestion	β_{123}	-0.0034	-1.9074	
	ASC	β_0	**0.5219**	**6.0175****	
	Time (Car)	β_4	**-0.0024**	**-3.0200****	
	Time (PT – Car)	β_5	**-0.0120**	**-17.7324****	
	Cost (Car – PT)	β_7	**-0.0115**	**-2.8378****	
	Cost (PT)	β_6	**-0.0803**	**-9.1564****	L(0) = - 10015.28
Model E1	**PT commuting cost subsidy**	β_1	**0.2979**	**14.4249****	$L(\hat{\beta})$= - 6982.509
	Additional parking fee	β_2	**-0.3803**	**-18.8976****	ρ^2= 0.303
	Congestion charge	β_3	**-0.3956**	**-22.4089****	Number of observations: 542
	Subsidy & Parking	β_{12}	**0.0292**	**4.5470****	
	Subsidy & Congestion	β_{13}	**0.0280**	**5.0957****	
	Parking & Congestion	β_{23}	**0.0349**	**6.0305****	
	Subsidy & Parking & Congestion	β_{123}	-0.0034	-1.9230	

	ASC	β_0	**-0.1643**	**-2.0269***	
	Time (Car)	β_4	-0.0006	-0.7985	
	Time (PT – Car)	β_5	**-0.0124**	**-17.7954****	
	Cost (Car – PT)	β_7	**-0.0184**	**-3.0716****	
	Cost (PT)	β_6	**-0.0768**	**-8.2459****	L(0) = - 10015.28
Model F1	**PT commuting cost subsidy**	β_1	**0.2746**	**11.9954****	$L(\hat{\beta})$= - 7278.90
	Additional parking fee	β_2	**-0.0846**	**-6.5567****	ρ^2= 0.273
	Congestion charge	β_3	**-0.2812**	**-19.4370****	Number of observations: 542
	Subsidy & Parking	β_{12}	-0.0017	-0.3367	
	Subsidy & Congestion	β_{13}	**0.0251**	**5.6589****	
	Parking & Congestion	β_{23}	**0.0082**	**2.7618****	
	Subsidy & Parking & Congestion	β_{123}	-0.0008	-0.8179	

Model G1	**ASC**	$\boldsymbol{\beta_0}$	**-0.1587**	**-1.9554***	L(0) = - 10015.28 L($\widehat{\beta}$)= - 7277.94 ρ^2= 0.270 Number of observations: 542
	Time (Car)	β_4	-0.0003	-0.3103	
	Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.0116**	**-16.8229****	
	Cost (Car – PT)	$\boldsymbol{\beta_7}$	**-0.0218**	**-3.6406****	
	Cost (PT)	$\boldsymbol{\beta_6}$	**-0.0756**	**-8.1371****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.2751**	**12.5532****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.0846**	**-6.7323****	
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.3102**	**-21.6001****	
	Subsidy & Parking	β_{12}	-0.0016	-0.3319	
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0257**	**6.2426****	
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0084**	**2.8969****	
	Subsidy & Parking & Congestion	β_{123}	-0.0008	-0.9042	
Model D2	**ASC**	$\boldsymbol{\beta_0}$	**0.4725**	**5.9129****	L(0) = - 10015.28 L($\widehat{\beta}$)= - 6983.38 ρ^2= 0.303 Number of observations: 542
	Time (Car)	$\boldsymbol{\beta_4}$	**-0.0024**	**-3.2860****	
	Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.0119**	**-17.6537****	
	Cost (Car – PT)	$\boldsymbol{\beta_7}$	**-0.0109**	**-2.6849****	
	Cost (PT)	$\boldsymbol{\beta_6}$	**-0.0810**	**-9.2221****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.2761**	**16.4734****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.3611**	**-20.7831****	
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.3721**	**-24.6811****	
	Subsidy & Parking	$\boldsymbol{\beta_{12}}$	**0.0199**	**4.6945****	
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0200**	**5.6447****	
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0280**	**6.2088****	
Model E2	**ASC**	$\boldsymbol{\beta_0}$	**0.4755**	**5.7335****	L(0) = - 10015.28 L($\widehat{\beta}$)= - 6984.133 ρ^2= 0.303 Number of observations: 542
	Time (Car)	$\boldsymbol{\beta_4}$	**-0.0024**	**-3.0078****	
	Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.0120**	**-17.7120****	
	Cost (Car – PT)	$\boldsymbol{\beta_7}$	**-0.0115**	**-2.8404****	
	Cost (PT)	$\boldsymbol{\beta_6}$	**-0.0799**	**-9.1172****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.2755**	**16.4360****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.3610**	**-20.7758****	
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.3787**	**-24.8031****	
	Subsidy & Parking	$\boldsymbol{\beta_{12}}$	**0.0198**	**4.6897****	
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0198**	**5.5877****	
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0279**	**6.2021****	
Model F2	**ASC**	$\boldsymbol{\beta_0}$	**-0.1955**	**-3.2266****	L(0) = - 10015.28 L($\widehat{\beta}$)= - 7280.903 ρ^2= 0.273 Number of observations: 542
	Time (Car)	$\boldsymbol{\beta_5}$	**-0.0127**	**-19.9081****	
	Cost (Car – PT)	$\boldsymbol{\beta_7}$	**-0.0215**	**-4.7264****	
	Cost (PT)	$\boldsymbol{\beta_6}$	**-0.0736**	**-9.0487****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.2795**	**19.9598****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.0864**	**-9.1158****	
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.2751**	**-22.6055****	
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0225**	**10.1317****	
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0064**	**2.8216****	
Model G2	**ASC**	$\boldsymbol{\beta_0}$	**-0.1694**	**-2.8044****	L(0) = - 10015.28 L($\widehat{\beta}$)= - 7317.464 ρ^2= 0.269 Number of observations: 542
	Time (Car)	$\boldsymbol{\beta_5}$	**-0.0117**	**-18.2701****	
	Cost (Car – PT)	$\boldsymbol{\beta_7}$	**-0.0230**	**-5.0123****	
	Cost (PT)	$\boldsymbol{\beta_6}$	**-0.0745**	**-9.2439****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.2798**	**19.9701****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.0863**	**-9.1006****	
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.3037**	**-24.3946****	
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0230**	**10.3205****	
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0065**	**2.8628****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

9.3.2. Calculation of utility value and choice probability of the travel mode

In the case of model D0, the utility value of car use can be estimated.

$$V_{car} = \beta_0 + \beta_4 \cdot \text{Car Commuting Time} + \beta_7 \cdot (\text{Car} - \text{PT}) \text{ Commuting Cost} + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j$$

$$V_{car} = (0.1263) + (-0.0023) \cdot \text{Car Commuting Time} + (-0.0108) \cdot (\text{Car} - \text{PT}) \text{ Commuting Cost} + (-0.2549) \cdot Park_j + (-0.2732) \cdot Congestion_j \quad (9\text{-}1)$$

The utility value of car use can be calculated by the method of substitution. For example, under the condition 13 [input value: $Subsidy_j$ (level one *2.212*), $Park_j$ (level one 2.5), $Congestion_j$ (level zero 0)], the utility of car use is calculated as follows:

$$V_{car} = (0.1263) + (-0.0023) \cdot (92.48) + (-0.0108) \cdot (6.411) + (-0.2549) \cdot (2.5) + (-0.2732) \cdot (0) = -0.79289,$$

$$U_{car} = e^{-0.79289} = 0.452535 \quad (9\text{-}2)$$

Table 9-5 shows the input values of the level of the MSP. The utility value of car use is 0.452535.

Table 9-5. Input values of the level of the MSP

Type of model	Level	Time		Cost		PT Commute cost subsidy	Additional parking fee	Congestion charge
		PT – Car	Car	Car – PT	PT			
		Minute	Minute	Won	Won	Won	Won	Won
Models D	0	28.58	92.48	6,411 (6.411)	4,422 (4.422)	0 (0)	0 (0)	0 (0)
	0.5	28.58	92.48	6,411 (6.411)	4,422 (4.422)	1106 (1.106)	1,250 (1.25)	1,500 (1.5)
	1	28.58	92.48	6,411 (6.411)	4,422 (4.422)	2211 (2.211)	2,500 (2.5)	3,000 (3)
	1.5	28.58	92.48	6,411 (6.411)	4,422 (4.422)	3317 (3.317)	3,750 (3.75)	4,500 (4.5)
	2	28.58	92.48	6,411 (6.411)	4,422 (4.422)	4422 (4.422)	5,000 (5)	6,000 (6)
Models E	0	28.58	92.48	6,411 (6.411)	4,422 (4.422)	0 (0)	0 (0)	0 (0)
	0.5	28.58	87.86	6,411 (6.411)	4,422 (4.422)	1106 (1.106)	1,250 (1.25)	1,500 (1.5)
	1	28.58	83.23	6,411 (6.411)	4,422 (4.422)	2211 (2.211)	2,500 (2.5)	3,000 (3)
	1.5	28.58	78.61	6,411 (6.411)	4,422 (4.422)	3317 (3.317)	3,75 (3.75)	4,500 (4.5)
	2	28.58	73.98	6,411 (6.411)	4,422 (4.422)	4422 (4.422)	5,000 (5)	6,000 (6)
Models F	0	28.58	92.48	4,483 (4.483)	4,422 (4.422)	0 (0)	1,250 (1.25)	670.8 (0.6708)
	0.5	28.58	92.48	4,483 (4.483)	4,422 (4.422)	1106 (1.106)	2,500 (2.5)	2,170.8(2.1708)
	1	28.58	92.48	4,483 (4.483)	4,422 (4.422)	2211 (2.211)	3,750 (3.75)	3,670.8(3.6708)
	1.5	28.58	92.48	4,483 (4.483)	4,422 (4.422)	3317 (3.317)	5,000 (5)	5,170.8(5.1708)
	2	28.58	92.48	4,483 (4.483)	4,422 (4.422)	4422 (4.422)	6,250 (6.25)	6,670.8(6.6708)
Models G	0	28.58	92.48	4,483 (4.483)	4,422 (4.422)	0 (0)	1,250 (1.25)	670.8 (0.6708)
	0.5	28.58	87.86	4,483 (4.483)	4,422 (4.422)	1106 (1.106)	2,500 (2.5)	2,170.8(2.1708)
	1	28.58	83.23	4,483 (4.483)	4,422 (4.422)	2211 (2.211)	3,750 (3.75)	3,670.8(3.6708)
	1.5	28.58	78.61	4,483 (4.483)	4,422 (4.422)	3317 (3.317)	5,000 (5)	5,170.8(5.1708)
	2	28.58	73.98	4,483 (4.483)	4,422 (4.422)	4422 (4.422)	6,250 (6.25)	6,670.8(6.6708)

The utility value of PT use can be estimated as follows.

$$V_{PT} = \beta_5 \cdot (\text{PT} - \text{Car}) \text{ Commuting Time}_i + \beta_6 \cdot \text{PT Commuting Cost}_i + \beta_1 \cdot Subsidy_j$$

$$V_{PT} = (-0.0118) \cdot (\text{PT} - \text{Car}) \text{ Commuting Time}_i + (-0.0810) \cdot \text{PT Commuting Cost}_i + (0.1821) \cdot Subsidy_j = (-0.0118) \cdot (28.58) + (-0.0810) \cdot (4.422) + (0.1821) \cdot (2.211) = -0.2928,$$

$$U_{PT} = e^{-0.2928} = 0.746174 \quad (9\text{-}3)$$

The utility value of PT use is 0.746174. In addition, the choice probability of PT use is 0.622481 (see **Table 9-6**).

$$P_{PT}^{i} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{0.746174}{0.452535+0.746174} = 0.622481 \cong \mathbf{62.25}\% \quad (9\text{-}4)$$

Table 9-6. Modal shift probability of PT in model D0 (unit: %)

Type of model	Policy level	PT commute cost subsidy	parking fee	Congestion charge	Subsidy & Parking	Subsidy & Congestion	Parking & Congestion	Subsidy & Parking & Congestion
Model D0	**0**	36.82	36.82	36.82	36.82	36.82	36.82	36.82
	0.25	39.19	40.6	41.71	43.05	44.17	45.62	48.13
	0.5	41.62	44.49	46.75	49.5	51.78	54.7	59.63
	0.75	44.08	48.45	51.87	55.97	59.31	63.48	70.16
	1	46.58	52.43	56.95	**62.25**	66.43	71.44	78.91
	1.25	49.09	56.38	61.89	68.14	72.87	78.27	85.63
	1.5	51.6	60.25	66.59	73.5	78.47	83.83	90.46
	1.75	54.11	64	70.98	78.24	83.19	88.18	93.79
	2	56.6	67.58	75.02	82.35	87.04	91.48	96

For reference, the utility values of the modified utility function correspond to those of the original utility function[14].

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[14] <The calculation of the choice probability by using separate model D0>

$U_{car} = \beta_0 + \beta_4 \cdot$Car Commuting Time$_i$ + $\beta_7 \cdot$(Car – PT) Commuting Cost $_i$ + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \varepsilon_{car}$

$U_{PT} = \beta_5 \cdot$(PT – Car) Commuting Time$_i$ + $\beta_6 \cdot$PT Commuting Cost$_i$ + $\beta_1 \cdot Subsidy_j + \varepsilon_{PT}$

Suppose no policy intervention, then

$V_{car} = 0.1263 + (-0.0023)\cdot(92.48) + (-0.0108)\cdot(6.411) = -0.155643$, $e^{-0.155643} = 0.855865$

$V_{PT} = (-0.0118)\cdot(28.58) + (-0.0810)\cdot(4.422) = -0.695426$, $e^{-0.695426} = 0.498862$

$$P_{car}^{i} = \frac{\exp(Vi,car)}{\exp(Vi,car)+\exp(Vi,PT)} = \frac{0.855865}{0.855865+0.498862} = 0.631762 \cong \mathbf{63.18\%}$$

$$P_{PT}^{i} = \frac{\exp(Vi,PT)}{\exp(Vi,car)+\exp(Vi,PT)} = \frac{0.498862}{0.855865+0.498862} = 0.368238 \cong \mathbf{36.82\%}$$

<The calculation of the choice probability by using an integrated model D0 >

$V_{car} - V_{PT} = \beta_0 + \beta_4 \cdot$Car Commuting Time + $\beta_7 \cdot$(Car – PT) Commuting Cost – $\beta_5 \cdot$(PT – Car) Commuting Time – $\beta_6 \cdot$PT Commuting Cost + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j - \beta_1 \cdot Subsidy_j$

$\rightarrow V_{car} - V_{PT} = 0.1263 + (-0.0023)\cdot(92.48) + (-0.0108)\cdot(6.411) - (-0.0118)\cdot(28.58) - (-0.0810)\cdot(4.422) = \mathbf{0.5397832}$

$= \beta_0 + \beta_4 \cdot$Car Commuting Time + $\beta_7 \cdot$Car Commuting Cost – $\beta_7 \cdot$PT Commuting Cost – $\beta_5 \cdot$PT Commuting Time + $\beta_5 \cdot$Car Commuting Time – $\beta_6 \cdot$PT Commuting Cost + $\beta_2 \cdot PPark_j + \beta_3 \cdot PCongestion_j - \beta_1 \cdot PSubsidy_j$

$= \beta_0 + \beta_4 \cdot$Car Commuting Time + $\beta_5 \cdot$Car Commuting Time – $\beta_7 \cdot$PT Commuting Cost – $\beta_6 \cdot$PT Commuting Cost + $\beta_7 \cdot$Car Commuting Cost – $\beta_5 \cdot$PT Commuting Time + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j - \beta_1 \cdot Subsidy_j$

$= \beta_0 + (\beta_4+\beta_5)\cdot$Car Commuting Time – $(\beta_7+\beta_6)\cdot$PT Commuting Cost + $\beta_7 \cdot$Car Commuting Cost – $\beta_5 \cdot$PT Commuting Time + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j - \beta_1 \cdot Subsidy_j$

$\rightarrow V_{car} - V_{PT} = 0.1263 + [(-0.0023) + (-0.0118)]\cdot(92.48) - [(-0.0108) + (-0.0810)]\cdot(4.422) + (-0.0108)\cdot(10.833^{*}) - (-0.0118)\cdot(121.06^{**}) = \mathbf{0.5397832}$, $e^{\mathbf{0.5397832}} = 1.715635$

$10.833^{*} = 6.411 + 4.422$, $121.06^{**} = 92.48 + 28.58$

$$P_{car}^{i} = \frac{1}{1+\{1/\exp\left(V_{i,j,car}\right)\}} = \frac{1}{1+\{1/\exp(\mathbf{0.5397832})\}} = \frac{1}{1+(\frac{1}{1.715635})} = 0.631762 \cong \mathbf{63.18\%}$$

$P_{PT}^{i} = 1 - P_{car}^{i} = 1 - 0.631762 = 0.368238 \cong \mathbf{36.82\%}$

9.3.3. Prediction of modal shift effects of modal shift policies

As indicated in **Figure 9-1**, in models D and models E, which are based on models putting the values of the 'current parking fee' (average 1,250 won) and the 'current toll' (average 670 won) into the '(Car – PT) Commuting Cost' variable, the market share of PT shows the same order of the magnitude of the modal shift effect as models that comprise only alternative-specific variables (i.e. models A, models B, and models C). In short, the orders of the modal shift probability of the MSP in models D and models E have the same results as those of models A, models B, and models C. In other words, in terms of the modal shift effects, the order of MSP is presented as follows: ① PT commuting cost subsidies & additional parking fees & congestion charges, ② additional parking fees & congestion charges, ③ PT commuting cost subsidies & congestion charges, ④ PT commuting cost subsidies & additional parking fees, ⑤ congestion charges, ⑥ additional parking fees, ⑦ PT commuting cost subsidies.

However, models F and models G, which are based on models putting the values of the 'current parking fee' and the 'current toll' into the 'alternative-specific variables (MSP)', not the '(Car – PT) Commuting Cost' variable, have different results from models A, models B, and models C. As shown in **Figure 9-2**, models F and models G show the different order of the modal shift effects. The orders of the modal shift effects of the MSP are presented as follows: ① PT commuting cost subsidies & additional parking fees & congestion charges, ② PT commuting cost subsidies & congestion charges, ③ additional parking fees & congestion charges, ④ congestion charges, ⑤ PT commuting cost subsidies & additional parking fees, ⑥ PT commuting cost subsidies, ⑦ additional parking fees. It can be inferred that models F and models G make the modal shift effects of the additional parking fees very weak. That is, the processing of input data such as the 'current parking fees' and the 'current tolls' seems to affect the modal shift effects of the additional parking fees substantially.

Figure 9-1. Comparison of the modal shift probability of the MSPs in models D and models E

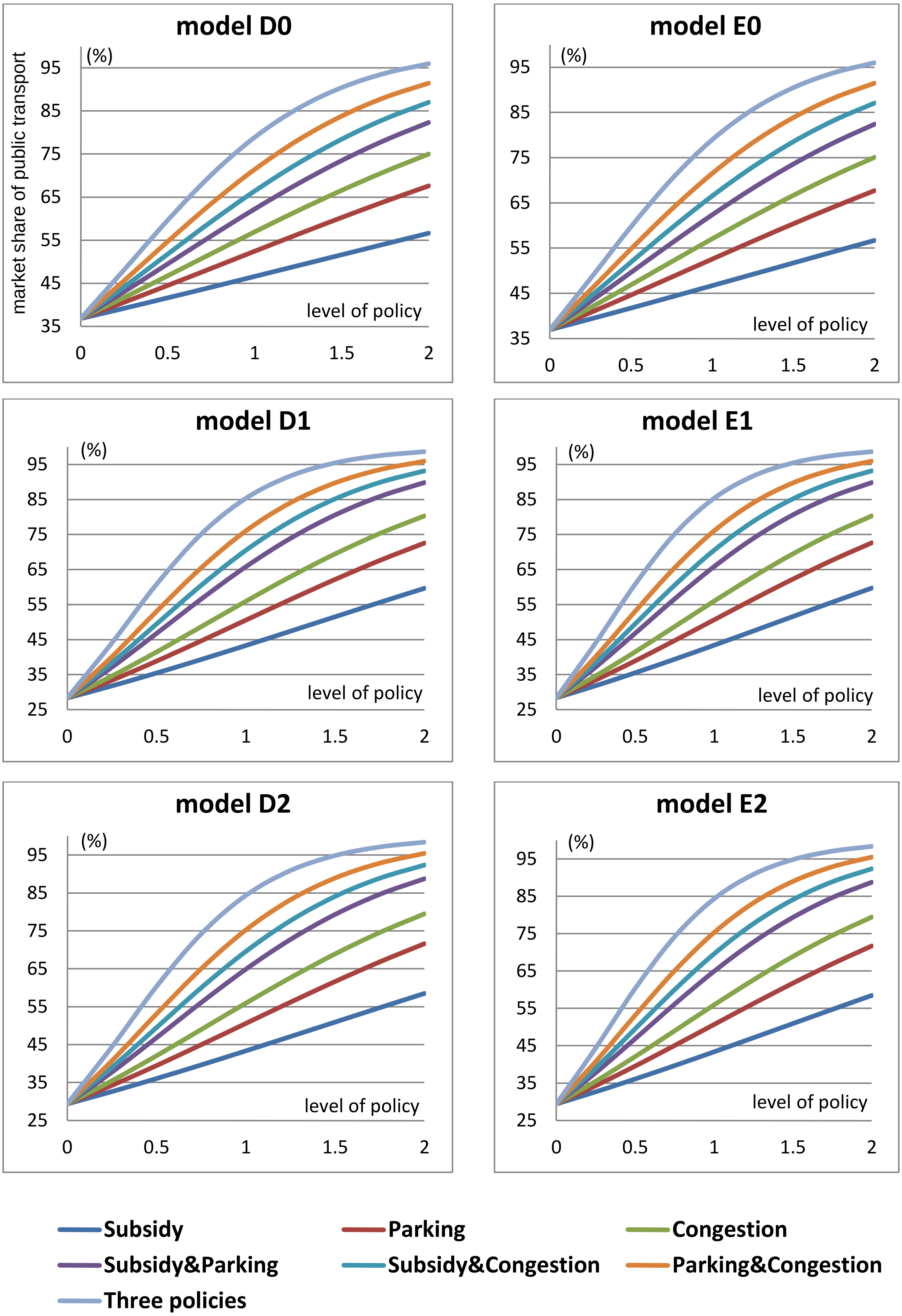
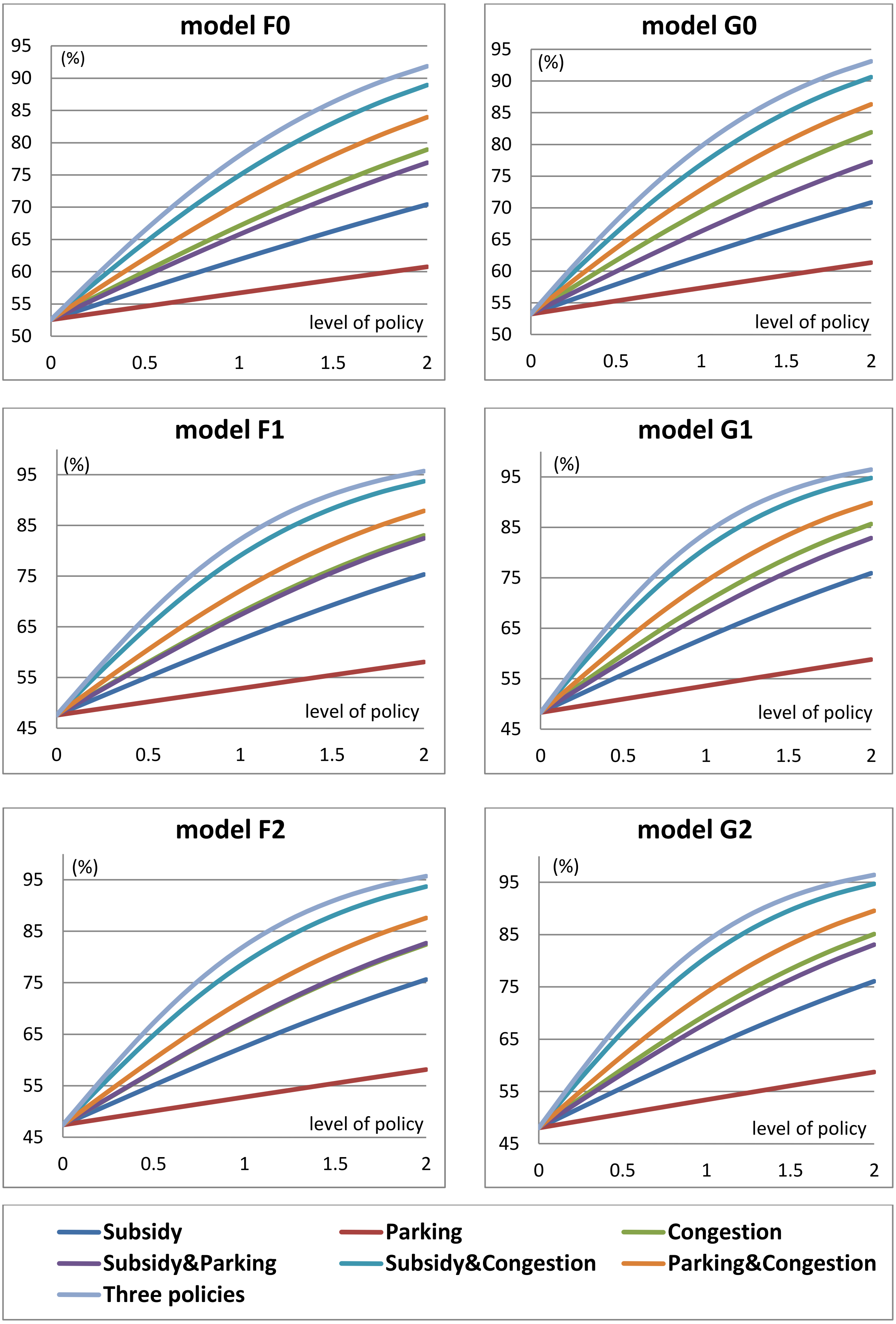


Figure 9-2. Comparison of the modal shift probability of the MSPs in models F and models G



9.3.4. Review of the difference between two types of the models

The reason for the weakened modal shift effects of the additional parking fees and congestion charges might attribute to the reflection of 'the current free parking fee and the free toll' into the 'alternative-specific variables (MSP)'. As shown in **Table 9-7** and **Table 9-8**, more than 75 % of respondents reveal that they used to enjoy free parking fee and the free toll in commuting patterns. It indicates that the majority of commuters using a private car would enjoy free parking in the workplace and would not use a toll road on the way to work.

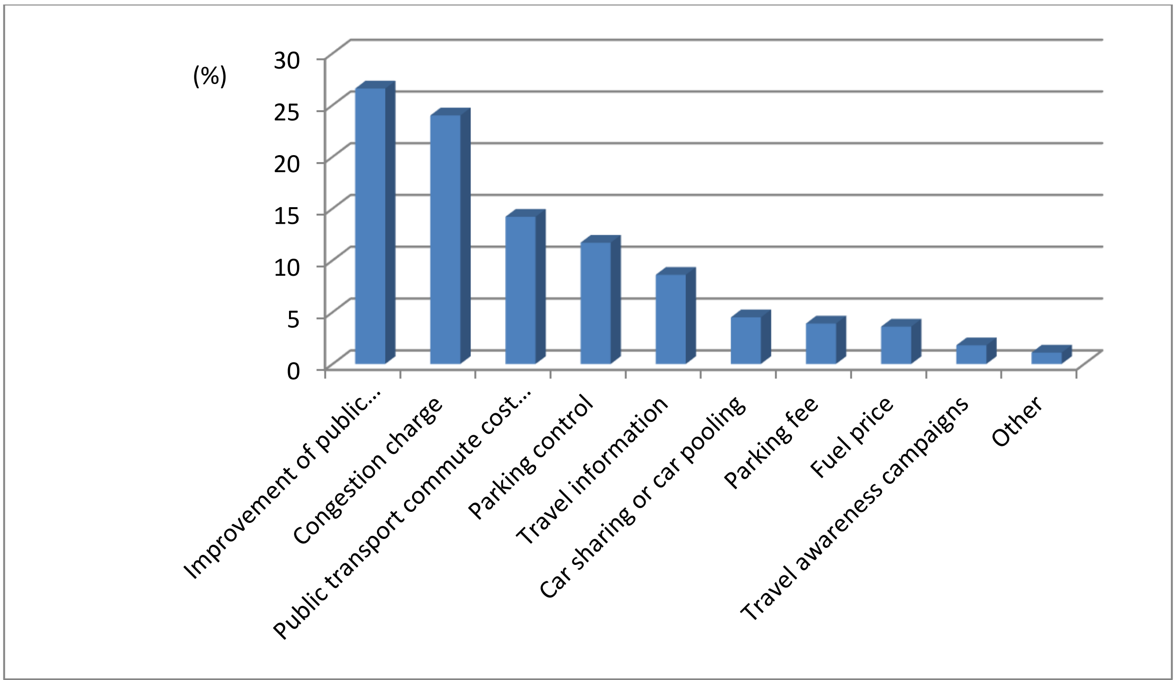
Table 9-7. Current parking fee payment

Classification	Segment	Frequency	Percent	Valid percent	Cumulative percent
Valid	**Free parking fee**	474	**61.8**	**76.7**	76.7
	Pay parking fee	144	18.8	23.3	100.0
	Total	618	80.6	100.0	
Missing		149	19.4		
Total		767	100.0		

Table 9-8. Current toll payment

Classification	Segment	Frequency	Percent	Valid percent	Cumulative percent
Valid	**No toll**	500	**65.2**	**80.8**	80.8
	Pay toll	119	15.5	19.2	100.0
	Total	619	80.7	100.0	
Missing		148	19.3		
Total		767	100.0		

Figure 9-3. What is the most effective and acceptable MSP in the short term (1-2 years)?



The modal shift probability of PT in models F and models G (see **Figure 9-2**) seems to match up to the responses in the optional type questionnaires in this research. Since models F and models G reflect the 'current free parking fee' and the 'current no toll' into the 'alternative-specific variables (MSP)', the influence of the current travel cost such as the 'current free parking fee' and the 'current no toll' seems to diminish the modal shift effect of additional parking fees and congestion charges. That is, models F and models G predict that the modal shift effects of the PT commuting cost subsidies would be stronger than those of additional parking fees. Meanwhile, in this survey, there are optional type questionnaires about the most effective and acceptable MSP in the short term. The responses in the optional type questionnaires indicate that policy preferences for the PT commuting cost subsidies are higher than the additional parking fees (see **Figure 9-3** and **Table 9-9**). These results accords with the prediction in models F and models G. In this sense, models F and models G can be regarded as more realistic models than models D and models E.

Table 9-9. Frequency analysis of optional type questionnaire (double check type)

Classifi -cation	Contents of answer	Frequency	Percent	Valid percent	Cumulative percent
Valid	Strengthening parking control	159	10.4	11.6	11.6
	Increasing parking fee	54	3.5	3.9	15.6
	Levying congestion charge	329	21.4	24.0	39.6
	Providing PT commute cost subsidy	194	12.6	14.2	53.8
	Increasing fuel price	49	3.2	3.6	57.4
	Holding travel awareness campaigns	24	1.6	1.8	59.1
	Stimulating car sharing or car pooling	61	4.0	4.5	63.6
	Providing more available travel information	118	7.7	8.6	72.2
	Improving the quality of PT service	365	23.8	**26.6**	98.9
	Other	15	1.0	1.1	100.0
	Total	1,368	89.2	100.0	
Missing		166	10.8		
Total	767*2 = 1534	1,534	100.0		

However, as for models F and model G, there is a risk of excessive reflection on the state of the 'current free parking fees' and the 'current no toll'. **Table 9-10** shows that the minority of respondents receive a commuting grant from their company. In this case, the main purpose of commute grant from the company seems not to be for the enhancement of PT use, but for the promotion of the use of a private car since employees usually receive a commuting grant as a type of car fuel cost or maintenance expenditure. Therefore, the data on commute grants from the company cannot be utilized as the current data relevant to the PT commuting cost subsidy. Considering the absence of the current data associated with the 'PT commuting cost subsidy', the influence of the 'current free parking fees' and the 'current no toll' may be overestimated in models F and models G. In conclusion, in order to avoid the influence of overestimation of particular data such as the 'current free parking fees' and the 'current no toll', models D and models E, which put the 'current free parking fees' and the 'current no toll' data into the '(Car – PT) Commuting Cost' variable, seem to be more desirable and acceptable models than models F and models G.

Table 9-10. Question: Does your company give you a commute grant?

Classification	Segment	Frequency	Percent	Valid percent	Cumulative percent
Valid	**Yes**	144	**18.8**	**19.2**	19.2
	No	606	79	80.8	100.0
	Total	750	97.8	100.0	
Missing		17	2.2		
Total		767	100.0		

9.3.5. Comparison of modal shift effects of modal shift policies at the same monetary level of policy intervention

The estimated market share of PT at the same monetary level of policy intervention can be obtained using the utility function. In this case, it is assumed that policy intervention of the combined MSPs is equally distributed. Models D and models E indicate that the greatest level of modal shift would be achieved by the introduction of congestion charges, with additional parking fees the next most effective, and the third most effective level of modal shift generated by a combination of additional parking fees and congestion charges. In addition, the lowest level of modal shift effect is generated by the PT commuting cost subsidies. In the other hand, the orders of the modal shift effect of the MSP in models F and models G indicate that the greatest level of modal shift would be achieved by the introduction of congestion charges, with the PT commuting cost subsidies the next most effective, and the third most effective level of modal shift generated by a union of the PT commuting cost subsidies and congestion charges. Especially, the lowest level of modal shift effect is generated by additional parking fees.

Let's review the choice probability of PT concerning the combined MSPs. If there are no interaction effects between the two MSPs, the modal shift probabilities might be approximate average values between the individual MSPs. If there are interaction effects between the two MSPs, the modal shift probabilities depend on the sign and the magnitude of coefficients of the combined MSPs. That is, the higher the value of the coefficients, the greater the degree of downward deviation from approximate average values between individual MSPs. This is mainly because all the coefficients related to the combined MSPs (i.e. β_{12}, β_{13}, and β_{23}) have positive signs.

9.4. Estimation Results of Mixed Logit Models with Commuting Time and Cost Variables

Table 9-11 compares the ρ^2 of the standard logit models with the MLMs (random coefficient models) with the normal distribution. The ρ^2 value of the MLM is not higher than that of the standard logit models apart from model D0. In general, the greater the number of parameter, the lower the value of ρ^2. The result is different from existing argument. Therefore, it can be inferred that the low ρ^2 of the MLM may result from the large increase of unimportant random effect coefficients in this research. This result indicates that the ρ^2 of the MLM is not always higher than the standard logit model. This result correponds to the existing study (Cherchi and Ortúzar, 2003), indicating that MLMs do not explain taste variations better than the standard logit models with interaction terms and some confounding effect may appear.

Table 9-11. Comparison of rho-squared index of models with commuting time and cost variables

Classification	Model D0	Model E0	Model D1	Model E1	Model D2	Model E2
Standard logit	0.298	0.298	0.303	0.303	0.303	0.303
Mixed logit (normal distribution)	0.306	0.240	0.266	0.254	0.265	0.269

In comparison with **Table 9-4** and **Table 9-12**, the estimated means in the MLM are higher than those of the standard logit models. In general, the absolute values of coefficients of the MLM are greater than those of the standard logit model. This may be mainly because the increase of the new estimated coefficients in the MLM stems from the part of the utility belonging to unobserved stochastic terms in the standard model.

Most of the coefficients, including means and standard deviations, are statistically significant in terms of the absolute t-value, with all such values larger than 2.57 and, therefore, significant at the 99% level. It means that almost all of the coefficients of explanatory variables have a statistically significant preference heterogeneity. In other words, the results from the MLM represent that most the variables are heterogeneous in the preference of travel mode. In particular, all the mean coefficients and standard deviation coefficients related to the interaction effect of the MSP are statistically significant in the various MLMs with commuting time and cost variables (i.e. model D1, model D2, model E1, and model E2). In the MLMs with commuting time and cost variables, all the coefficients of the interaction effect of the MSP seem to have substantial explanatory power and preference heterogeneity across individuals. In addition, it indicates that the coefficients of the interaction effect of the MSP should be included in the specification of the MLMs.

Since the standard deviation coefficients are highly significant, the coefficients vary in the population. However, there are four exceptions. That is, four standard deviation coefficients (random effect coefficients) are statistically insignificant since the absolute t-value is less than 1.65. In particular, since most standard deviation coefficients related to the interaction terms of the MSPs are statistically significant in the various MLMs with commuting time and cost variables (i.e. model D1, model D2, model E1, and model E2), the interaction effects of the MSPs seem to be heterogeneous across individuals.

Meanwhile, in the case of model E1, since the standard deviation coefficient (7.1240) of the 'Subsidy & Parking & Congestion' variable shows the highest value in model E1, it can be interpreted that this variable is the most flexible factor that has taste heterogeneity.

Table 9-12. Estimation result of mixed logit models with normal distribution

Model	Coefficient	Beta	Value	t-value	Goodness of fit
Model D0	**ASC**	β_0	**0.8917**	**6.4755****	L(0) = - 10015.28 L(β) = - 6951.3 ρ^2 = 0.306 Number of observations: 542
	Time (Car) (Mean)	β_4	**-0.0032**	**-2.9784****	
	Random effect (SD)		-0.0002	-0.0334	
	Time (PT – Car) (Mean)	β_5	**-0.0166**	**-11.3770****	
	Random effect (SD)		**0.0119**	**2.8830****	
	Cost (Car – PT) (Mean)	β_7	**-0.0152**	**-2.2136***	
	Random effect (SD)		0.0236	0.7311	
	Cost (PT) (Mean)	β_6	**-0.0575**	**-3.8625****	
	Random effect (SD)		-0.0747	-1.5572	
	PT commuting cost subsidy(Mean)	β_1	**0.4778**	**10.2736****	
	Random effect (SD)		**0.4415**	**7.3988****	
	Additional parking fee (Mean)	β_2	**-0.4475**	**-10.8245****	
	Random effect (SD)		**0.3492**	**6.1294****	
	Congestion charge (Mean)	β_3	**-0.4562**	**-11.5433****	
	Random effect (SD)		**0.2675**	**5.5558****	

Model D1	**ASC**	β_0	**77.5590**	**156.2570****	L(0) = - 10015.28 L(β) = - 7356.1 ρ^2 = 0.266 Number of observations: 542
	Time (Car) (Mean)	β_4	**-0.9148**	**-159.7920****	
	Random effect (SD)		**1.5844**	**270.5250****	
	Time (PT – Car) (Mean)	β_5	**-0.6966**	**-189.4280****	
	Random effect (SD)		**1.1726**	**207.2240****	
	Cost (Car – PT) (Mean)	β_7	**-0.2829**	**-15.0110****	
	Random effect (SD)		**2.0545**	**34.9870****	
	Cost (PT) (Mean)	β_6	**-4.1136**	**-213.6990****	
	Random effect (SD)		**1.7416**	**56.6330****	
	PT commuting cost subsidy(Mean)	β_1	**17.8850**	**352.4330****	
	Random effect (SD)		**1.9202**	**47.2600****	
	Additional parking fee (Mean)	β_2	**-20.5483**	**-205.7700****	
	Random effect (SD)		**3.3275**	**15.8870****	
	Congestion charge (Mean)	β_3	**-21.1407**	**-215.6790****	
	Random effect (SD)		**3.4497**	**23.5650****	
	Subsidy & Parking (Mean)	β_{12}	**0.9516**	**101.5910****	
	Random effect (SD)		**2.4327**	**236.5300****	
	Subsidy & Congestion (Mean)	β_{13}	**0.8788**	**79.5220****	
	Random effect (SD)		**2.1949**	**166.9050****	
	Parking & Congestion (Mean)	β_{23}	**1.6392**	**57.0470****	
	Random effect (SD)		**3.9804**	**150.1760****	
	Subsidy & Parking & Congestion (Mean)	β_{123}	**-0.7558**	**-144.6120****	
	Random effect (SD)		**2.5248**	**325.5910****	

Model D2	ASC	β_0	64.1127	41.7612**	L(0) = - 10015.28 L(β) = - 7362.9 ρ^2 = 0.265 Number of observations: 542
	Time (Car) (Mean)	β_4	-0.7888	-48.2526**	
	Random effect (SD)		1.4292	121.6042**	
	Time (PT – Car) (Mean)	β_5	-0.5643	-93.9420**	
	Random effect (SD)		1.0448	117.2499**	
	Cost (Car – PT) (Mean)	β_7	-0.2319	-4.4893**	
	Random effect (SD)		2.0817	13.1399**	
	Cost (PT) (Mean)	β_6	-3.8457	-86.3074**	
	Random effect (SD)		1.4804	42.2504**	
	PT commuting cost subsidy (Mean)	β_1	14.3227	178.1075**	
	Random effect (SD)		1.0832	20.3209**	
	Additional parking fee (Mean)	β_2	-16.7639	-87.8318**	
	Random effect (SD)		3.2254	7.8947**	
	Congestion charge (Mean)	β_3	-17.2767	-95.3880**	
	Random effect (SD)		2.5715	7.7784**	
	Subsidy & Parking (Mean)	β_{12}	0.4765	41.0997**	
	Random effect (SD)		2.1973	136.3895**	
	Subsidy & Congestion (Mean)	β_{13}	0.4730	38.6056**	
	Random effect (SD)		2.0908	95.6617**	
	Parking & Congestion (Mean)	β_{23}	1.0385	22.8291**	
	Random effect (SD)		3.7234	69.3059**	

Model E0	ASC	β_0	260.4558	2126.8570**	L(0) = - 10015.28 L(β) = - 7609.1 ρ^2 = 0.240 Number of observations: 542
	Time (Car) (Mean)	β_4	-4.0324	-943.4433**	
	Random effect (SD)		-3.8596	-1156.2513**	
	Time (PT – Car) (Mean)	β_5	-1.7326	-1155.3743**	
	Random effect (SD)		-2.4236	-1044.5159**	
	Cost (Car – PT) (Mean)	β_7	-1.0239	-175.0172**	
	Random effect (SD)		4.2534	227.9069**	
	Cost (PT) (Mean)	β_6	-11.6061	-1050.4186**	
	Random effect (SD)		-0.0385	-3.8956**	
	PT commuting cost subsidy (Mean)	β_1	41.7645	1321.1972**	
	Random effect (SD)		-2.8189	-185.5847**	
	Additional parking fee (Mean)	β_2	-38.2410	-1146.3810**	
	Random effect (SD)		29.7001	542.0706**	
	Congestion charge (Mean)	β_3	-45.2341	-1264.1124**	
	Random effect (SD)		25.3128	607.2189**	

Model E1	ASC	β_0	115.1476	630.7710**	L(0) = - 10015.3 L(β) = - 7475.1 ρ^2 = 0.254 Number of observations: 542
	Time (Car) (Mean)	β_4	-1.3792	-460.0770**	
	Random effect (SD)		2.0249	672.3610**	
	Time (PT – Car) (Mean)	β_5	-1.1137	-645.5760**	
	Random effect (SD)		2.2597	711.2360**	
	Cost (Car – PT) (Mean)	β_7	-0.7543	-98.1450**	
	Random effect (SD)		1.6115	47.6880**	
	Cost (PT) (Mean)	β_6	-5.8092	-495.1040**	
	Random effect (SD)		3.2403	196.0200**	
	PT commuting cost subsidy (Mean)	β_1	28.2649	749.2090**	
	Random effect (SD)		4.9388	215.8100**	
	Additional parking fee (Mean)	β_2	-32.5176	-703.6460**	
	Random effect (SD)		2.2435	25.9590**	
	Congestion charge (Mean)	β_3	-33.4022	-679.1480**	
	Random effect (SD)		4.2829	61.2560**	
	Subsidy & Parking (Mean)	β_{12}	1.3495	171.3080**	
	Random effect (SD)		6.2681	630.7140**	
	Subsidy & Congestion (Mean)	β_{13}	1.1350	132.3920**	
	Random effect (SD)		5.5285	572.8560**	
	Parking & Congestion (Mean)	β_{23}	2.4780	191.1370**	
	Random effect (SD)		5.5792	475.8970**	
	Subsidy & Parking & Congestion (Mean)	β_{123}	-1.5431	-434.7130**	
	Random effect (SD)		7.1240	953.3770**	

Model E2	**ASC**	β_0	**58.5611**	**90.9572****	L(0) = - 10015.3 L(β) = - 7321.7 ρ^2 = 0.269 Number of observations: 542
	Time (Car) (Mean)	β_4	**-0.8444**	**-110.8627****	
	Random effect (SD)		**1.1252**	**135.9338****	
	Time (PT – Car) (Mean)	β_5	**-0.6707**	**-129.6212****	
	Random effect (SD)		**1.5594**	**197.9249****	
	Cost (Car – PT) (Mean)	β_7	**-0.6486**	**-23.9859****	
	Random effect (SD)		**-1.8779**	**-16.3322****	
	Cost (PT) (Mean)	β_6	**-4.7608**	**-180.1026****	
	Random effect (SD)		**2.2601**	**61.3398****	
	PT commuting cost subsidy (Mean)	β_1	**16.2673**	**284.2857****	
	Random effect (SD)		**9.7698**	**236.9828****	
	Additional parking fee (Mean)	β_2	**-19.1829**	**-167.8847****	
	Random effect (SD)		0.0697	0.2799	
	Congestion charge (Mean)	β_3	**-19.3579**	**-178.7696****	
	Random effect (SD)		**0.5391**	**2.6760****	
	Subsidy & Parking (Mean)	β_{12}	**0.4292**	**51.2028****	
	Random effect (SD)		**5.8422**	**258.2336****	
	Subsidy & Congestion (Mean)	β_{13}	**0.2692**	**37.7351****	
	Random effect (SD)		**4.6183**	**250.4772****	
	Parking & Congestion (Mean)	β_{23}	**1.5305**	**57.9862****	
	Random effect (SD)		**1.3382**	**23.8063****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

9.5. Summary

Twelve models with commuting time and cost variables are developed since travel time and cost are major variables, significantly affecting travel mode choice. Models with time and cost variables are based on a daily trip. Time and cost data are obtained from the survey. Models with commuting time and cost variables include ‘Car Commuting Time’, ‘PT Commuting Cost’, ‘(PT – Car) Commuting Time’, and ‘(Car – PT) Commuting Cost’ variable. Three main criteria are used according to whether the current tolls and the current parking fees are included in the ‘alternative-specific variables’ or the ‘(Car – PT) Commuting Cost’ variable, whether the values of reductions in commuting time of congestion charges are reflected in a model or not, and whether the interaction terms are taken into consideration or not.

The main two types of models consist of one model in which the current tolls and the current parking fees are reflected in the ‘(Car – PT) Commuting Cost’ variable and the other model in which these values are included in the ‘alternative-specific variables’.

For the former models (i.e. models D and models E), the orders of the modal shift effect of the MSP are the same as those of the models comprising only alternative-specific variables (i.e. models A, models B, and models C). However, as for the latter models (i.e. models F and models G), the orders of the modal shift effect of the MSP are different from those of models with alternative-specific variables (i.e. models A, models B, and models C). That is, out of the three main MSPs, congestion charging is still superior to the other MSPs in terms of modal shift effects. However, the modal shift effects of PT commuting cost subsidies are more powerful than those of additional parking fees. In particular, the modal shift effects of congestion charges are stronger than a combination of PT commuting cost subsidies and additional parking fees despite the double input of policy intervention. In addition, the order of the modal shift effect of the combined MSPs is also changed. The modal shift impact of the bond of PT commuting cost subsidies and congestion charges is superior to that of the combination of additional parking fees and congestion charges.

To account for individual’s preference heterogeneity in the model, the MLMs with commuting time and cost variables are also developed. However, in comparison of the ρ^2 value in the MLMs and the standard logit models, the MLMs seem to be not always better than the standard logit models.

Chapter 10. Development of Covariate Models

10.1. Introduction

The purpose of this chapter is to develop models with additional covariates. This chapter consists of seven further sections. Section 10.2 considers not only the specification of models, but also various covariate variables. Section 10.3 reviews a default model with additional covariates and specifies the form of utility functions. Section 10.4 creates a covariate model with attitudinal factors. Section 10.5 also develops a covariate model with socio-economic factors. Section 10.6 constructs a covariate model with travel factors. Section 10.7 calibrates a synergistic covariate model with all the additional covariates such as attitudinal, socio-economic and travel factors. Section 10.8 develops the mixed logit models with additional covariate variables.

10.2. Consideration of Developing Covariate Models

In this study, one of the main subjects is to understand what factors affect commuter's transport mode choice patterns. If there are some factors affecting the choice of travel mode, these factors should be included in the transport choice models with additional covariates. The utility function of travel mode can be specified as follows (Lee et al., 2005; Yannis and Antoniou, 2007):

$$U_{i,car} = V_{i,car} + \varepsilon_{i,car} = \alpha_{transit} \cdot D_i + \beta_1 \cdot Subsidy_j + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j + \sum_{j=1}^{n} r_j \cdot X_i + \varepsilon_{i,car} \quad (10\text{-}1)$$

- $\alpha_{transit}$: the parameter estimates with regard to the variable of travel mode characteristic D_i
- X_i: the variables of individual, social or travel characteristics affecting the choice of travel mode (the *i*-th observation on all of the covariates)
- r_j: the parameter estimates with respect to the variables X_i to incorporate the effects of covariates

The one advantage of using a logit model is that the utility function can include various independent variables without the limitation of the unit. Various independent variables can go into the model provided that they are specified in methods that construct difference in utility over alternatives (Train, 2003). Since a wide variety of additional covariates can put into a logit model, it is possible to analyse the realistic choice behaviour of commuters. That is, whenever the researcher thinks that some factors are more likely to affect the use of travel mode, the factor can be captured in a logit model. Although these characteristics can be functioned as explanatory variables, these variables are not relevant to alternative-specific variables. “Logit models can capture taste variations” (Train, 1986). Consequently, by developing models with diverse explanatory variables, the question can be answered: Why do commuters choose a particular transport mode and what factors influence the mode choice patterns in South Korea?

Although there are numerous factors affecting commuter’s mode choice behaviour, the key factors can be classified into attitudinal, socio-economic, and travel characteristics. The chosen possible explanatory variables as RP data have been reflected in the survey design to understand how explanatory variables affect the choice of travel mode. In general, the selection of covariates is crucial to investigating the important explanatory variables. Possible key factors were selected in terms of the intensity of the modal shift effect.

10.3. A Default Model with Additional Covariates

Model E1, which is a model with interaction terms, having commuting time and cost variables, and putting the ‘current car parking fee’ value and the ‘current toll’ value into the ‘(Car – PT) Commuting Cost’ variables, has been selected as the default model. In this case, a model with interaction terms can study the interaction effect of MSPs in covariate models. Additionally, a model with commuting time and cost variables can review the role of representative traditional generic variables. A model reflecting the current travel costs into the ‘(Car – PT) Commuting Cost’ variable can allow the comparison of basic models (models A, models B, and models C) as the same type of input models.

Covariate variables should be attributed to the utility of car use to appropriately develop covariate models without the overlapping calculation of covariate variables. That is, since additional individual covariates should be allowed to interact with alternative-specific variables, the covariate variables should have real values when choosing a car whereas the covariate variables have zero when choosing PT. **Table 10-1** shows forms of utility functions.

Table 10-1. Forms of utility function

Model E1	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$ {(Car – PT) Commuting Cost$_i$ 〔= (Car – PT) Commuting Cost + current car parking fee + current car toll〕 – Reduced commuting time effect of congestion charge policy$_{i,car}$ (if level 1=0.1, if level 2=0.2)} + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j$
Model H1	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$ {(Car – PT) Commuting Cost$_i$ 〔= (Car – PT) Commuting Cost + current car parking fee + current car toll〕 – Reduced commuting time effect of congestion charge policy$_{i,car}$(if level 1=0.1, if level 2=0.2)} + $\beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j + \beta_{Q1} \cdot Q1 + \beta_{Q2} \cdot Q2 + \beta_{Q3} \cdot Q3 + \beta_{Q4} \cdot Q4 + \beta_{Q5} \cdot Q5 + \beta_{Q6} \cdot Q6 + \beta_{Q7} \cdot Q7$

Model H2	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$Car Commuting Time$_i$ + $\beta_7 \cdot${(Car – PT) Commuting Cost$_i$ 〔= (Car – PT) Commuting Cost + current car parking fee + current car toll〕 – Reduced commuting time effect of congestion charge policy$_{i,car} \cdot$(if level 1=0.1, if level 2=0.2)} + $\beta_2 \cdot Park_j$ + $\beta_3 \cdot Congestion_j$ + $\beta_{12} \cdot Subsidy_j \cdot Park_j$ + $\beta_{13} \cdot Subsidy_j \cdot Congestion_j$ + $\beta_{23} \cdot Park_j \cdot Congestion_j$ + $\beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j$ + $\beta_{region} \cdot DRegion$ + $\beta_{gender} \cdot DGender$ + $\beta_{age40} \cdot DAge40$ + $\beta_{age50} \cdot DAge50$ + $\beta_{income2} \cdot DIncome2$ + $\beta_{income3} \cdot DIncome3$ + $\beta_{income4} \cdot DIncome4$ + $\beta_{edu1} \cdot DEdu$ + $\beta_{edu2} \cdot DEdu2$ + $\beta_{work1} \cdot DWork$ + $\beta_{work2} \cdot DWork2$ + $\beta_{work3} \cdot DWork3$ + $\beta_{household2} \cdot Dhousehold2$ + $\beta_{household3} \cdot Dhousehold\ 3$ + $\beta_{household4} \cdot Dhousehold\ 4$ + $\beta_{household5} \cdot Dhousehold\ 5$ + $\beta_{child} \cdot DChild$
Model H3	$V_{i,\,car} = \beta_0 + \beta_4 \cdot$Car Commuting Time$_i$ + $\beta_7 \cdot${(Car – PT) Commuting Cost$_i$ 〔= (Car – PT) Commuting Cost + current car parking fee + current car toll〕 – Reduced commuting time effect of congestion charge policy$_{i,car}$(if level 1=0.1, if level 2=0.2)} + $\beta_2 \cdot Park_j$ + $\beta_3 \cdot Congestion_j$ + $\beta_{12} \cdot Subsidy_j \cdot Park_j$ + $\beta_{13} \cdot Subsidy_j \cdot Congestion_j$ + $\beta_{23} \cdot Park_j \cdot Congestion_j$ + $\beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j$ + $\beta_{car\ parking\ time} \cdot$*Car parking time* + $\beta_{car\ walking\ time} \cdot$*Car walking time* + $\beta_{PT\ waiting\ time} \cdot$*PT waiting time* + $\beta_{main\ commute\ time} \cdot$*DMain commute time* + $\beta_{commute\ support\ from\ company} \cdot$*DCommute Support from company*
Common	$V_{i,\,PT} = \beta_5 \cdot$(PT – Car) Commuting Time$_i$ + $\beta_6 \cdot$PT Commuting Cost$_i$ + $\beta_1 \cdot Subsidy_j$

10.4. Development of a Covariate Model with Attitudinal factors

Frequency distribution of individual perception and attitude is shown in **Table 7-10**. In addition, **Table 10-2** compares a covariate model with attitudinal factors (i.e. model H1) with a default model (i.e. model E1). The ρ^2 value of model H1 (0.369) is higher than that of model E1 (0.303). Due to the inclusion of attitudinal covariates, model H1 seems to become a more appropriate model rather than model E1 in terms of the goodness of fit.

In **Table 10-2**, the signs of the coefficients involving individual perception and attitude (β_{Q1}, β_{Q2}, β_{Q3}, β_{Q4}, β_{Q5}, β_{Q6}, and β_{Q7}) represent the relationship between individual perception and car use. For example, the relationship between 'Q1' (Congestion problems are very severe during the morning peak) and 'car use' is positive. It can be interpreted that the respondent who feels the severity of congestion problems tends to use a car on average. For another instance, the relationship between 'Q2' (the use of PT is important in order to reduce global warming and to protect the environment) and 'car use' is negative. It indicates that people who acknowledge the importance of PT use for the environment tend to use PT rather than a car. In addition, since the sign of the coefficient (β_{Q7}) is negative, it can be inferred that there is a reverse relationship between 'the consciousness of importance of cost' and 'car use'. Meanwhile, the sign of the coefficient β_{Q3} is negative, whereas the ones of the coefficients β_{Q4}, β_{Q5}, and β_{Q6} are positive.

As shown in **Table 10-2**, the coefficient value of β_7 (– 0.0115) involving the 'Cost (Car – PT)' variable in model E1 is statistically significant at the 99% confidence interval since the absolute t-value (– 2.8378) is greater than 2.57. However, the coefficient value of β_7 (0.0037) in model H1 is statistically insignificant since the absolute t-value (0.8525) is less than 1.96. In this case, due to the influence of the attitudinal covariate 'Q7' (Cost is a very important factor in determining commuting), the 'Cost (Car – PT)' variable seems to lose statistical significance in model H1. In addition, the coefficient value of β_{Q6} (0.0507) in model H1 is statistically insignificant since the absolute t-value (1.5362) is less than 1.96. In this case, since the 'Car Commuting Time' (β_4) and the '(PT – Car) Commuting Time' (β_5) variable might influence the coefficient β_{Q6}, the 'Q6' (Time is a very important factor in determining commuting) variable seems to lose statistical significance in model H1. In addition, the coefficient β_{123} (– 0.0033) in model H1 is not acceptable in terms of statistics since the absolute t-value (– 1.7371) is less than 1.96.

Table 10-2. Estimation result of a covariate model with attitudinal factors (model H1) and a default model (model E1)

Type of model	Coefficient	Beta	Value	t-value	Goodness of fit
Model E1	**Alternative-Specific Constant**	$\boldsymbol{\beta_0}$	**0.5219**	**6.0175****	L(0) = - 10015.28 L($\widehat{\beta}$)= - 6982.51 ρ^2= 0.303 Number of observations: 542
	Time (Car)	$\boldsymbol{\beta_4}$	**-0.0024**	**-3.0200****	
	Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.0120**	**-17.7324****	
	Cost (Car – PT)	$\boldsymbol{\beta_7}$	**-0.0115**	**-2.8378****	
	Cost (PT)	$\boldsymbol{\beta_6}$	**-0.0803**	**-9.1564****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.2979**	**14.4249****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.3803**	**-18.8976****	
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.3956**	**-22.4089****	
	Subsidy & Parking	$\boldsymbol{\beta_{12}}$	**0.0292**	**4.5470****	
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0280**	**5.0957****	
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0349**	**6.0305****	
	Subsidy & Parking &Congestion	β_{123}	-0.0034	-1.9230	
Model H1	**Alternative-Specific Constant**	$\boldsymbol{\beta_0}$	**2.5286**	**9.4603****	L(0) = - 9590.38 L($\widehat{\beta}$)= - 6054.99 ρ^2= 0.369 Number of observations: 519
	Time (Car)	$\boldsymbol{\beta_4}$	**-0.0045**	**-5.1512****	
	Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.0084**	**-11.4971****	
	Cost (Car – PT)	β_7	0.0037	0.8525	
	Cost (PT)	$\boldsymbol{\beta_6}$	**-0.1055**	**-10.9065****	
	PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.3413**	**14.9895****	
	Additional parking fee	$\boldsymbol{\beta_2}$	**-0.4298**	**-19.5513****	
	Congestion charge	$\boldsymbol{\beta_3}$	**-0.4528**	**-23.4180****	
	Subsidy & Parking	$\boldsymbol{\beta_{12}}$	**0.0315**	**4.4275****	
	Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0315**	**5.2174****	
	Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0390**	**6.2460****	
	Subsidy & Parking & Congestion	β_{123}	-0.0033	-1.7371	
	Q1 (congestion severity)	$\boldsymbol{\beta_{Q1}}$	**0.0670**	**2.1726***	
	Q2 (environmental awareness)	$\boldsymbol{\beta_{Q2}}$	**-0.4161**	**-12.6770****	
	Q3 (health awareness)	$\boldsymbol{\beta_{Q3}}$	**-0.0572**	**-2.3844****	
	Q4 (freedom from regulation)	$\boldsymbol{\beta_{Q4}}$	**0.2494**	**10.4541****	
	Q5 (importance of convenience)	$\boldsymbol{\beta_{Q5}}$	**0.3270**	**9.5929****	
	Q6 (importance of time)	β_{Q6}	0.0507	1.5362	
	Q7 (importance of cost)	$\boldsymbol{\beta_{Q7}}$	**-0.6891**	**-24.0351****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Since model H1 is composed of unstandardized coefficients, comparison of coefficients cannot provide accurately relative influence of explanatory variables. To accurately gauge the relative importance of explanatory variables in the logit model, standardized estimated coefficients can be utilized (Carpio et al., 2007). Standardized coefficients can answer the question of which independent variable has a greater influence on the dependent variable when the variables are measured in different units of measurement. In general, since many model estimations are usually carried out on unstandardized variables, unstandardized coefficients are produced. Each variable can be standardized so that its variance is one. Each variable can be standardized by subtracting the mean from each value of the variable and then dividing by its standard deviation (Gelman, 2008). Therefore, **Table 10-3** represents the standardized coefficients in model H1.

Table 10-3. The standardized coefficients of model H1

Coefficient	Beta	Value	t-value	Goodness of fit
Alternative-Specific Constant	$\boldsymbol{\beta_0}$	**-2.4146**	**-20.7012****	
Time (Car)	$\boldsymbol{\beta_4}$	**-0.1304**	**-4.2881****	
Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.2915**	**-11.2795****	
Cost (Car – PT)	β_7	0.0512	1.6393	
Cost (PT)	$\boldsymbol{\beta_6}$	**-0.1185**	**-3.0509****	
PT commuting cost subsidy	β_1	0.0503	1.6270	
Additional parking fee	$\boldsymbol{\beta_2}$	**-0.5328**	**-22.3706****	
Congestion charge	$\boldsymbol{\beta_3}$	**-0.7001**	**-29.0836****	L(0) = - 9590.38
Subsidy & Parking	β_{12}	0.0273	1.3921	L($\widehat{\beta}$)= - 6054.99
Subsidy & Congestion	β_{13}	0.0350	1.7830	ρ^2= 0.369
Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.1477**	**6.2030****	Number of observations: 519
Subsidy & Parking & Congestion	β_{123}	0.0030	0.1523	
Q1 (congestion severity)	$\boldsymbol{\beta_{Q1}}$	**0.0670**	**2.2164***	
Q2 (environmental awareness)	$\boldsymbol{\beta_{Q2}}$	-0.4015	**-12.4546****	
Q3 (health awareness)	$\boldsymbol{\beta_{Q3}}$	**-0.0533**	**-2.2631***	
Q4 (reluctance of regulation)	$\boldsymbol{\beta_{Q4}}$	**0.2387**	**10.2517****	
Q5 (importance of convenience)	$\boldsymbol{\beta_{Q5}}$	**0.3144**	**9.4223****	
Q6 (importance of time)	β_{Q6}	0.0462	1.4280	
Q7 (importance of cost)	$\boldsymbol{\beta_{Q7}}$	-0.6602	**-23.5712****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Since the absolute value (**– 0.6602**) of the coefficient β_{Q7} is the highest out of all the attitudinal factors and the sign of coefficient β_{Q7} is negative, it can be inferred that there is the greatest reverse relationship between 'the consciousness of importance of cost' and 'car use'. In addition, since the absolute value (**– 0.4015**) of the coefficient β_{Q2} is the next highest, it can be inferred that there is the second strongest reverse relationship between 'the consciousness of the importance of PT use for the environment' and 'car use'.

10.5. Development of a Covariate Model with Socio-economic Factors

10.5.1. Frequency analysis and meaning of socio-economic factors

The data of the socio-economic variables, which are the RP data as self-reported data from the questionnaire, can be possible explanatory variables (see **Table 10-4**).

Table 10-4. Frequency analysis of covariate variables

Variable	Classification	Frequency (number)	Percent	Valid percent
Region	Seoul	466	60.8	61.2
	Outside of Seoul	296	38.6	38.8
	Total	762	99.4	100
	Missing	5	0.6	
Gender	Male	647	84.4	85.1
	Female	113	14.7	14.9
	Total	760	99.1	100
	Missing	7	0.9	
Age	20-30s	283	36.9	37.3
	40s	346	45.1	45.6
	50s+	130	17.0	17.1
	Total	759	99	100
	Missing	8	1	
Education	Below university	47	6.1	6.2
	Undergraduate	493	64.3	64.7
	Postgraduate	222	28.9	29.1
	Total	762	99.3	100
	Missing	5	0.7	
Work	Other	146	19.0	19.1
	Specialized	171	22.3	22.4
	Administrative	319	41.6	41.8
	Technical	127	16.6	16.7
	Total	763	99.5	100
	Missing	4	0.5	
Income	Up to ₩3,000,000	74	9.6	9.7
	₩3,000,001~5,000,000	269	35.1	35.2
	₩5,000,001~7,000,000	225	29.3	29.4
	More than ₩7,000,001	196	25.6	25.7
	Total	764	99.6	100
	Missing	3	0.4	
Household size	1	38	5.0	5.0
	2	78	10.2	10.2
	3	185	24.1	24.2
	4	366	47.7	48.0
	5+	96	12.5	12.6
	Total	763	99.5	100
	Missing	4	0.5	
Child	Having child or children	377	49.2	49.6
	Not having child	383	49.9	50.4
	Total	760	99.1	100
	Missing	7	0.9	
Total		767	100	

In general, if a respondent corresponds to the dummy variable, the value of the dummy variable will be one, otherwise zero. *DRegion, DGender, DAge 40, DAge 50, DIncome 2, DIncome 3, DIncome 4, DEdu 1, DEdu 2, DWork 1, DWork 2, DWork 3, Dhousehold 2, Dhousehold 3, Dhousehold 4, Dhousehold 5*, and *DChild* are dummy variables (see **Table 10-1** and **Figure 10-1**).

Figure 10-1. Meaning of socio-economic factors

・Region (Do you live outside of Seoul? In Seoul: No [0], Outside of Seoul: Yes [1])

・Gender (Are you female? Male: No [0], Female: Yes [1])

・Age (How old are you? 20s-30s: [0], 40s: [Age40], More than 50s: [Age50])
Age 40: Are you in your 40s? No [0], Yes [1]
Age 50: Are you in your 50 or more? No [0], Yes [1]

・Income (What is your total household income from all sources before tax per month?
Up to 3,000,000 won: [0], 3,000,001~5,000,000 won: [Income2], 5,000,001~7,000,000 won: [Income 3], More than 7,000,0001 won: [Income 4])

Income 2: Is your total household income between 3,000,001 and 5,000,000 won? No [0], Yes [1]

Income 3: Is your total household income between 5,000,001 and 7,000,000 won? No [0], Yes [1]

Income 4: Is your total household income more than 7,000,000 won? No [0], Yes [1]

・Education (What is your highest educational career?
Below university: [0], Undergraduate: [Edu1], Postgraduate: [Edu2])

Edu 1: Are your highest education career undergraduate? No [0], Yes [1]

Edu 2: Are your highest education career graduate? No [0], Yes [1]

・Work (What is your occupational sector? Other sector: [0], Specialized sector: [Work1], Administrative sector: [Work2], Technical sector: [Work3])

Work1: Do you work in a specialized sector? No [0], Yes [1]

Work2: Do you work in the administrative sector? No [0], Yes (1]

Work3: Do you work in the technical sector? No [0], Yes [1]

・Household size (What is your household size? One: [0], Two: [Household2], Three: [Household3], Four: [Household4], Five: [Household5])

Household2: Is your household size two? No [0], Yes [1]

Household3: Is your household size three? No [0], Yes [1]

Household4: Is your household size four? No [0], Yes [1]

Household5: Is your household size five? No [0], Yes [1]

・Child (Do you have a child or children who commute to schools, nurseries or infant caring facilities? Not having a child: No [0], Having a child: Yes [1])

10.5.2. Estimation result of a covariate model with socio-economic factors

The ρ^2 value of model H2 (0.328) with socio-economic factors is higher than the default model E1 (0.303). In **Table 10-5**, since the absolute t-value of β_7, β_{123}, β_{edu2}, and β_{work1} are less than 1.96, the coefficients are unacceptable in terms of statistics. However, the rest of the coefficients are statistically significant. In addition, while the signs of the coefficients β_{region}, $\beta_{work2,}$ β_{work3}, $\beta_{household2}$, $\beta_{household3}$, $\beta_{household4}$, $\beta_{household5}$, and β_{child} are negative, the ones of coefficients β_{gender}, β_{age40}, β_{age50}, $\beta_{income2}$, $\beta_{income3}$, $\beta_{income4}$, β_{edu1}, β_{edu2}, and β_{work1} are positive. For example, because the sign of $\beta_{income4}$ is positive, there is a positive relationship between 'the income 4 group' and 'car use'. That is, if a respondent belongs to the group of an individual whose total household income is more than 7,000,000 won, the respondent's utility of car use would increase. In this case, since *DIncome 4* (see **Figure 10-1**) is an indicator, the value of *DIncome 4* will be one. Therefore, the utility value of the dummy variable ($\beta_{income\ 4}\cdot DIncome\ 4$) would be 0.8078 (= 0.8078×1) in the utility function. Conversely, if a respondent does not belong to this group, the value of *DIncome 4* would be zero.

Table 10-5. Estimation result of a covariate model with socio-economic factors (model H2)

Coefficient	Beta	Value	t-value	Goodness of fit
Alternative-Specific Constant	β_0	0.1427	0.7824	
Time (Car)	$\boldsymbol{\beta_4}$	**-0.0019**	**-2.1751***	
Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.0124**	**-16.3327****	
Cost (Car – PT)	β_7	-0.0075	-1.6709	
Cost (PT)	$\boldsymbol{\beta_6}$	**-0.0939**	**-9.5788****	
PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.3112**	**14.4898****	
Additional parking fee	$\boldsymbol{\beta_2}$	**-0.4017**	**-19.2394****	
Congestion charge	$\boldsymbol{\beta_3}$	**-0.4154**	**-22.7060****	
Subsidy & Parking	$\boldsymbol{\beta_{12}}$	**0.0296**	**4.4665****	
Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0286**	**5.0899****	
Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0377**	**6.3207****	
Subsidy & Parking & Congestion	β_{123}	-0.0032	-1.7446	
Region	$\boldsymbol{\beta_{region}}$	**-0.1255**	**-2.2688***	L(0) = - 9611.87
Gender	$\boldsymbol{\beta_{gender}}$	**0.4105**	**5.8398****	L($\widehat{\beta}$)= - 6459.30
Age40	$\boldsymbol{\beta_{age40}}$	**0.3459**	**5.7560****	ρ^2= 0.328
Age50	$\boldsymbol{\beta_{age50}}$	**0.2952**	**3.9334****	Number of observations: 520
Income2	$\boldsymbol{\beta_{income2}}$	**0.2041**	**2.1330***	
Income3	$\boldsymbol{\beta_{income3}}$	**0.4297**	**4.2690****	
Income4	$\boldsymbol{\beta_{income4}}$	**0.8078**	**7.7427****	
Edu1	$\boldsymbol{\beta_{edu1}}$	**0.3347**	**3.2095****	
Edu2	β_{edu2}	0.1836	1.7186	
Work1	β_{work1}	0.1169	1.7574	
Work2	$\boldsymbol{\beta_{work2}}$	**-0.5800**	**-9.1410****	
Work3	$\boldsymbol{\beta_{work3}}$	**-0.3925**	**-5.1424****	
Household2	$\boldsymbol{\beta_{house2}}$	**-0.3539**	**-2.8294****	
Household3	$\boldsymbol{\beta_{house3}}$	**-0.2269**	**-1.9629***	
Household4	$\boldsymbol{\beta_{house4}}$	**-0.2476**	**-2.1849***	
Household5	$\boldsymbol{\beta_{house5}}$	**-0.3362**	**-2.5898****	
Child	$\boldsymbol{\beta_{child}}$	**-0.1355**	**-2.6737****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Table 10-6 shows the standardized coefficients of model H2. As shown in **Table 10-6**, the value (0.7822) of $\beta_{income4}$ is the highest out of all the socio-economic factors. Therefore, it can be interpreted that the impact of the income variable affecting the choice of travel mode is the strongest in all socio-economic factors in model H2. The sign of the coefficient $\beta_{income4}$ is positive. Therefore, it can be inferred that there is the strongest affirmative relationship between the 'high-income group' and 'car use'. Meanwhile, the absolute value (– 0.5610) of β_{work2} is the next highest out of all the socio-economic factors and the sign of coefficient β_{work2} is negative. Therefore, it can be inferred that there is a very strong reverse relationship between the 'workers in the administrative sector' and 'car use'. It suggests that people working in the administrative sector tend to use PT rather than a private car.

Table 10-6. The standardized coefficients of model H2

Coefficient	Beta	Value	t-value	Goodness of fit
Alternative-Specific Constant	$\boldsymbol{\beta_0}$	**-1.6023**	**-10.3319****	
Time (Car)	β_4	-0.0162	-0.5316	
Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.4384**	**-16.1575****	
Cost (Car – PT)	β_7	-0.0480	-1.5067	
Cost (PT)	β_6	-0.0336	-0.8461	
PT commuting cost subsidy	β_1	0.0393	1.2939	
Additional parking fee	$\boldsymbol{\beta_2}$	**-0.4928**	**-21.5254****	
Congestion charge	$\boldsymbol{\beta_3}$	**-0.6529**	**-28.3176****	
Subsidy & Parking	β_{12}	0.0306	1.6098	
Subsidy & Congestion	β_{13}	0.0329	1.7249	
Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.1443**	**6.2655****	
Subsidy & Parking & Congestion	β_{123}	0.0008	0.0406	
Region	$\boldsymbol{\beta_{region}}$	**-0.1192**	**-2.2206***	L(0) = - 9611.87
Gender	$\boldsymbol{\beta_{gender}}$	**0.4025**	**5.8139****	$L(\widehat{\beta})$= - 6459.30
Age40	$\boldsymbol{\beta_{age40}}$	**0.3376**	**5.7426****	ρ^2= 0.328
Age50	$\boldsymbol{\beta_{age50}}$	**0.2811**	**3.8118****	Number of observations: 520
Income2	$\boldsymbol{\beta_{income2}}$	**0.1960**	**2.0871***	
Income3	$\boldsymbol{\beta_{income3}}$	**0.4140**	**4.1873****	
Income4	$\boldsymbol{\beta_{income4}}$	**0.7822**	**7.6342****	
Edu1	$\boldsymbol{\beta_{edu1}}$	**0.3195**	**3.1176****	
Edu2	β_{edu2}	0.1769	1.6848	
Work1	β_{work1}	0.1146	1.7487	
Work2	$\boldsymbol{\beta_{work2}}$	**-0.5610**	**-8.9685****	
Work3	$\boldsymbol{\beta_{work3}}$	**-0.3746**	**-5.0158****	
Household2	$\boldsymbol{\beta_{house2}}$	**-0.3427**	**-2.8039****	
Household3	$\boldsymbol{\beta_{house3}}$	**-0.2230**	**-1.9743***	
Household4	$\boldsymbol{\beta_{house4}}$	**-0.2409**	**-2.1766***	
Household5	$\boldsymbol{\beta_{house5}}$	**-0.3388**	**-2.6669****	
Child	$\boldsymbol{\beta_{child}}$	**-0.1358**	**-2.7308****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

10.6. Development of a Covariate Model with Travel Factors

10.6.1. Frequency analysis and meaning of travel factors

Since the rate of the missing data is over 20%, some explanatory variables are excluded in the development of the model. These explanatory variables related to the characteristics of a commute journey that have too many missing data might cause the deterioration of a logit model. As shown in **Table 10-7** (see blue coloured cell), the covariates in which the rate of missing data is high are excluded in the process of the model estimation. Due to the characteristics of the survey, there are limitations of using data. For example, the respondent who does not transfer in commuting journey cannot participate in the question of asking the number of the transfer. Since covariate models should be estimated by only the data that have no missing values, the limitation of data usage for the covariate models is greater than other models.

Table 10-7. Frequency analysis of travel factors

Information on travel factor	Mean	Sd	Number of missing data	Rate of missing data
Rate of car parking time	8.29	6.66	124	16.1%
Rate of car walking time	9.19	6.28	124	16.1%
Rate of PT waiting time	12.83	8.20	94	12.3%
Rate of PT transfer time	13.14	8.63	377	49.2%
Number of transfer	1.35	0.58	390	50.8%
Frequency of car use (weekly)	3.17	1.83	187	24.3%
Main commute time			6	0.8%
Commute support from company			17	2.2%

In terms of characteristics of explanatory variables, the generic variables such as 'Car Commuting Time', '(Car – PT) Commuting Cost', '(PT – Car) Commuting Time', and 'PT Commuting Cost' can be classified as a kind of travel factors in this research. In the utility function, *DMain commute time*, *DCommute Support from company* variables are dummy variables. **Table 10-8** illustrates frequency analysis of travel factors. In addition, **Figure 10-2** shows the meaning of travel factors.

Table 10-8. Frequency analysis of travel factors

Variable	Content	Frequency (number)	Percent	Valid percent
Main commute time	Before 8 am	232	30.2	30.5
	After 8 am	529	69.0	69.5
	Total	761	99.2	100
	Missing	6	0.8	
Commute support from company	Having	606	79.0	80.8
	Not having	144	18.8	19.2
	Total	750	97.8	100
	Missing	17	2.2	

Figure 10-2. Meaning of travel factors

Car parking time (rate of car parking time out of total commute time of car usage)

Car walking time (rate of car waiting time out of total commute time of car usage)

PT waiting time (rate of PT waiting time out of total commute time of PT usage)

Main commute time (Is your main commute time after 8 am? Before 8 am: no [0], After 8 am: Yes[1])

Commute Support from company (Does your company support you in terms of commute cost? No [0], Yes [1])

10.6.2. Estimation result of a covariate model with travel factors

In terms of the goodness of fit of the estimated model, the ρ^2 value of model H3 (0.323) with travel factors is higher than the default model E1 (0.303). In **Table 10-9**, since the absolute t-values of β_7 and $\beta_{car\ walking\ time}$ are less than 1.96, these variables are unacceptable in terms of statistics. However, the rest of coefficients are statistically significant in model H3. While the sign of coefficients $\beta_{car\ parking\ time}$ is negative, the ones of coefficients $\beta_{car\ walking\ time}$, $\beta_{PT\ waiting\ time}$, $\beta_{main\ commute\ time}$, and $\beta_{commute\ support\ from\ company}$ are positive. Through the signs of the coefficients, the relationship between travel factors and the utility of car use can be understood. For example, because the sign of $\beta_{car\ parking\ time}$ is negative, there is a reverse relationship between 'the rate of car parking time' and 'car use'. That is, if the ratio of car parking time is higher, the utility of car use will be decreased.

Table 10-9. Estimation result of a covariate model with travel factors (model H3)

Coefficient	Beta	Value	t-value	Goodness of fit
Alternative-Specific Constant	β_0	0.2367	1.8231	L(0) = - 9280.55 L($\widehat{\beta}$)= - 6986.69 ρ^2= 0.323 Number of observations: 502
Time (Car)	$\boldsymbol{\beta_4}$	**-0.0054**	**-5.7449****	
Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.0112**	**-15.4384****	
Cost (Car – PT)	β_7	0.0007	0.1652	
Cost (PT)	$\boldsymbol{\beta_6}$	**-0.1005**	**-10.6505****	
PT commuting cost subsidy	$\boldsymbol{\beta_1}$	**0.3189**	**14.4679****	
Additional parking fee	$\boldsymbol{\beta_2}$	**-0.3918**	**-18.4664****	
Congestion charge	$\boldsymbol{\beta_3}$	**-0.4216**	**-22.4466****	
Subsidy & Parking	$\boldsymbol{\beta_{12}}$	**0.0320**	**4.6643****	
Subsidy & Congestion	$\boldsymbol{\beta_{13}}$	**0.0306**	**5.2263****	
Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.0370**	**6.0412****	
Subsidy & Parking & Congestion	$\boldsymbol{\beta_{123}}$	**-0.0039**	**-2.0655***	
Car parking time (%)	$\boldsymbol{\beta_{car\ parking\ time}}$	**-0.0099**	**-2.6352****	
Car walking time (%)	$\beta_{car\ walking\ time}$	0.0003	0.0776	
PT waiting time (%)	$\boldsymbol{\beta_{PT\ waiting\ time}}$	**0.0187**	**6.7455****	
Main commute time	$\boldsymbol{\beta_{commute\ time}}$	**0.3539**	**6.7403****	
Commute support from company	$\boldsymbol{\beta_{commute\ support}}$	**0.1631**	**2.9523****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

As shown in **Table 10-10**, the value (0.3398) of $\beta_{commute\ time}$ is the highest out of all the travel factors. Therefore, it indicates that the impact of 'main departure time' variable affecting the choice of travel mode is very much stronger than the other travel factors in model H3. Since the sign of the coefficient $\beta_{commute\ time}$ is positive, it can be inferred that there is the strongest affirmative relationship between 'the main commute time' and 'car use'. It means that people whose main commute time is after 8 am tend to prefer the use of a car.

Table 10-10. The standardized coefficients of model H3

Coefficient	Beta	Value	t-value	Goodness of fit
Alternative-Specific Constant	$\boldsymbol{\beta_0}$	**-1.7506**	**-25.0444****	L(0) = - 9280.55 L($\widehat{\beta}$)= - 6986.69 ρ^2= 0.323 Number of observations: 502
Time (Car)	$\boldsymbol{\beta_4}$	**-0.1482**	**-4.4587****	
Time (PT – Car)	$\boldsymbol{\beta_5}$	**-0.3960**	**-15.2410****	
Cost (Car – PT)	β_7	0.0185	0.6041	
Cost (PT)	$\boldsymbol{\beta_6}$	**-0.1061**	**-2.7869****	
PT commuting cost subsidy	β_1	0.0495	1.6264	
Additional parking fee	$\boldsymbol{\beta_2}$	**-0.4761**	**-20.3951****	
Congestion charge	$\boldsymbol{\beta_3}$	**-0.6450**	**-27.5032****	
Subsidy & Parking	β_{12}	0.0285	1.4821	
Subsidy & Congestion	β_{13}	0.0304	1.5771	
Parking & Congestion	$\boldsymbol{\beta_{23}}$	**0.1336**	**5.6829****	
Subsidy & Parking & Congestion	β_{123}	-0.0033	-0.1713	
Car parking time (%)	$\boldsymbol{\beta_{C\ parking\ time}}$	**-0.0097**	**-2.6123****	
Car walking time (%)	$\beta_{C\ walking\ time}$	-0.0001	-0.0251	
PT waiting time (%)	$\boldsymbol{\beta_{PT\ waiting\ time}}$	**0.0177**	**6.5520****	
Main commute time	$\boldsymbol{\beta_{commute\ time}}$	**0.3398**	**6.6383****	
Commute support from company	$\boldsymbol{\beta_{commute\ support}}$	**0.1553**	**2.8645****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

10.7. Development of a Model with All the Additional Covariates

10.7.1. Development of a synergistic covariate model

The utility function with all the additional covariates can be developed as in **Table 10-11**. In model H4, additional covariates cover socio-economic, travel, and attitudinal factors. That is, the default model E1 is added by several kinds of covariates to compare the influence of all the explanatory variables. The comparison of all the explanatory variables can allow the understanding of what factors affect the commuter's travel mode choice.

Table 10-11. Utility function of model H4

$U_{i,\,car} = \beta_0 + \beta_4 \cdot$ Car Commuting Time$_i$ + $\beta_7 \cdot$ {(Car – PT)·Commuting Cost$_i$ [= (Car – PT) Commuting Cost + current car parking fee + current car toll] – Reduced commuting time effect of congestion charge policy$_{i,car}$ (if level 1=0.1, if level 2=0.2)} + $\beta_2 \cdot$ *Park$_j$* + $\beta_3 \cdot$ *Congestion$_j$* + $\beta_{12} \cdot$ *Subsidy$_j$·Park$_j$* + $\beta_{13} \cdot$ *Subsidy$_j$·Congestion$_j$* + $\beta_{23} \cdot$ *Park$_j$·Congestion* + $\beta_{123} \cdot$ *Subsidy$_j$·Park$_j$·Congestion* + $\beta_{region} \cdot$ *DRegion* + $\beta_{gender} \cdot$ *DGender* + $\beta_{age40} \cdot$ *DAge40* + $\beta_{age50} \cdot$ *DAge50* + $\beta_{income2} \cdot$ *DIncome2* + $\beta_{income3} \cdot$ *DIncome3* + $\beta_{income4} \cdot$ *DIncome4* + $\beta_{edu1} \cdot$ *DEdu* + $\beta_{edu2} \cdot$ *DEdu2* + $\beta_{work1} \cdot$ *Work1* + $\beta_{work2} \cdot$ *Work2* + $\beta_{work3} \cdot$ *Work3* + $\beta_{household2} \cdot$ *Dhousehold2* + $\beta_{household3} \cdot$ *Dhousehold3* + $\beta_{household4} \cdot$ *Dhousehold4* + $\beta_{household5} \cdot$ *Dhousehold5* + $\beta_{child} \cdot$ *DChild* + $\beta_{car\ parking\ time} \cdot$ *Car parking time ratio* + $\beta_{car\ walking\ time} \cdot$ *Car walking time ratio* + $\beta_{PT\ waiting\ time} \cdot$ *PT waiting time ratio* + $\beta_{main\ commute\ time} \cdot$ *DMain commute time* + $\beta_{commute\ support\ from\ company} \cdot$ *D Commute Support from company* + $\beta_{Q1} \cdot$ Q1 + $\beta_{Q2} \cdot$ Q2 + $\beta_{Q3} \cdot$ Q3 + $\beta_{Q4} \cdot$ Q4 + $\beta_{Q5} \cdot$ Q5 + $\beta_{Q6} \cdot$ Q6 + $\beta_{Q7} \cdot$ Q7 + $\varepsilon_{i,\,car}$
$U_{i,\,PT} = \beta_5 \cdot$ (PT – Car)·Commuting Time$_i$ + $\beta_6 \cdot$ PT Commuting Cost$_i$ + $\beta_1 \cdot$ *Subsidy$_j$* + $\varepsilon_{i,\,PT}$

10.7.2. Estimation results of a synergistic covariate model comprising only statistically significant coefficients

Model H4 is developed as a synergistic covariate model comprised of only statistically significant coefficients (see **Table 10-12**). In terms of the goodness of fit of the estimated model, the ρ^2 value of model H4 (0.423) is higher than that of model E1 (0.303), model H1 (0.328), model H2 (0.369), and model H3 (0.323). It means that model H4 is a very good appropriate model. In addition, all the coefficients are reasonably significant with expected signs in the sense of explaining travel mode choice behaviour.

Figure 10-3 shows the choice probability of PT in model H4 at the same monetary level of policy intervention. In terms of the order of modal shift effects, the estimation result of model H4 is the same as that of the models with alternative-specific variables (i.e. models A, models B, and models C).

Table 10-12. Estimation result of a covariate model with all the factors (model H4)

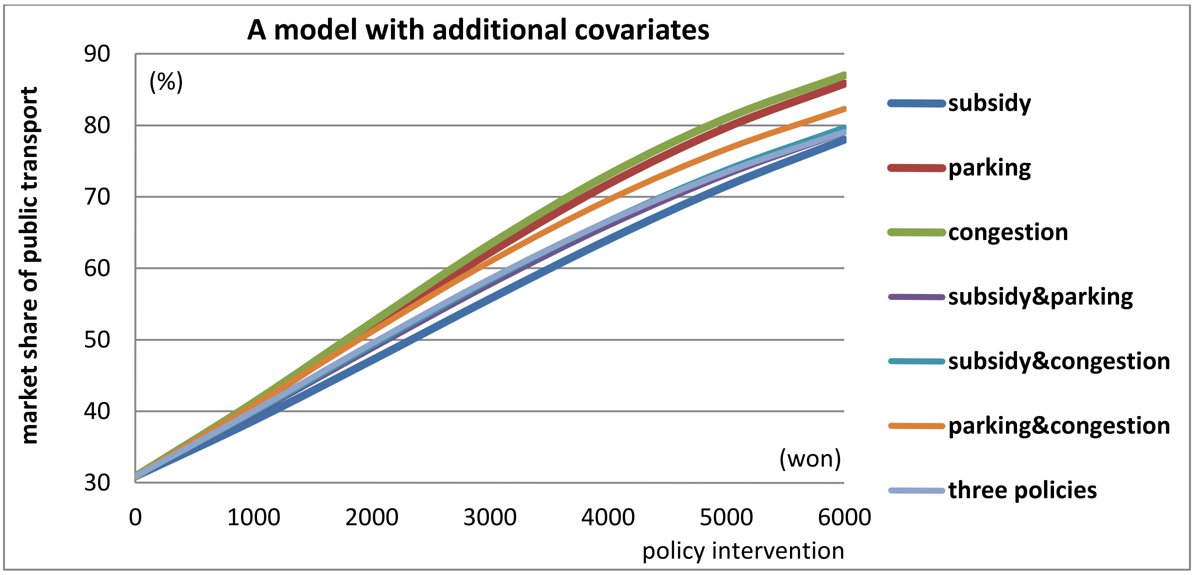
Coefficient	Beta	Value	t-value	Goodness of fit
Alternative-Specific Constant	β_0	**2.3652**	**8.3063****	
Time (Car)	β_4	**-0.0045**	**-4.6834****	
Time (PT – Car)	β_5	**-0.0101**	**-12.0226****	
Cost (PT)	β_6	**-0.1276**	**-11.7592****	
PT commuting cost subsidy	β_1	**0.3474**	**17.1948****	
Additional parking fee	β_2	**-0.4350**	**-21.3367****	
Congestion charge	β_3	**-0.4655**	**-25.7321****	
Subsidy & Parking	β_{12}	**0.0232**	**4.6291****	
Subsidy & Congestion	β_{13}	**0.0239**	**5.7156****	
Parking & Congestion	β_{23}	**0.0350**	**6.6404****	
Region (no:0, outside of Seoul:1)	β_{region}	**-0.1654**	**-2.7474****	
Age40 (no:0, 40s:1)	β_{age40}	**0.3079**	**5.6911****	L(0) = - 9087.85
Income3 (no:0, 5000-7000T won:1)	$\beta_{income3}$	**0.6092**	**10.0648****	L($\hat{\beta}$) = - 5242.83
Income4 (no:0, more than 7,000T won:1)	$\beta_{income4}$	**0.6574**	**10.0617****	ρ^2= 0.423
Edu1 (no:0, undergraduate:1)	β_{edu1}	**0.2179**	**4.0572****	Number of observations:
Work2 (no:0, administrative sector:1)	β_{work2}	**-0.6926**	**-12.3593****	494
Work3 (no:0, technical sector:1)	β_{work3}	**-0.4905**	**-6.4720****	
Household4 (no:0, family number 4:1)	β_{house4}	**-0.1255**	**-2.4169***	
Child (no:0, having a child:1)	β_{child}	**-0.1325**	**-2.4739***	
Car parking time ratio	$\beta_{C\ parking\ time}$	**-0.0185**	**-4.5270****	
PT waiting time ratio	$\beta_{PT\ waiting\ time}$	**0.0207**	**6.7096****	
Main commute time (no:0, after 8am:1)	$\beta_{commute\ time}$	**0.2030**	**3.4397****	
Support from company (no:0, yes:1)	$\beta_{commute\ support}$	**0.1743**	**2.7705****	
Q2 (environmental awareness)	β_{Q2}	**-0.4203**	**-13.7475****	
Q4 (freedom from regulation)	β_{Q4}	**0.3210**	**12.0838****	
Q5 (importance of convenience)	β_{Q5}	**0.3199**	**8.2624****	
Q7 (importance of cost)	β_{Q7}	**-0.7638**	**-23.9342****	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

* Superscript * represents significance within 5%.

Figure 10-3. The choice probability of PT usage with model H4 at the same monetary level of policy intervention



* Zero (meaning the default values) inserts into every dummy variable

Table 10-13 shows the standardized coefficients in model H4. Through **Table 10-13**, the relative importance of explanatory variables can be understood. In a comparison of the standardized coefficients, the main effects of MSP have the most powerful influence on travel mode choice. The coefficient value of the congestion charges is – 0.7958, the additional parking fees – 0.5690, and PT commuting cost subsidies 0.5862. It indicates that the ‘alternative-specific variables’ (level of MSP) have the most powerful influence on mode choice. An interesting finding is that the attitudinal factors seem to be the next most effective explanatory variables. The consciousness of the importance of cost (coefficient value: – 0.6338), the environmental protection (– 0.3319), and the freedom from regulation (0.3324) shows the high values of the coefficients respectively. The coefficient value (β_6) of ‘PT Commuting Cost’ variable is – 0.3938. In addition, the coefficient value (β_5) of the ‘Time (PT – Car)’ variables is – 0.3625. The coefficient β_{work2} (– 0.3416) related to whether people who work in the administrative sector or not has a significant influence on the choice of travel mode. Therefore, it can be inferred that the commuter’s occupational influence is relatively large. In addition, the coefficient $\beta_{income4}$ (total household income is more than 7,000,000 won) is 0.2873. The coefficient $\beta_{income3}$ (total household income is between 5,000,001 and 7,000,000 won) is 0.2776.

Table 10-13. The standardized coefficients of model H4

Coefficient	Beta	Value	t-value	Goodness of fit
Alternative-Specific Constant	β_0	**1.6335**	**55.1062****	
Time (car)	β_4	**-0.1624**	**-4.6066****	
Time (PT – car)	β_5	**-0.3625**	**-12.0544****	
Cost (PT)	β_6	**-0.3938**	**-11.7364****	
PT commuting cost subsidy	β_1	**0.5862**	**17.4042****	
Additional parking fee	β_2	**-0.5690**	**-21.3577****	
Congestion charge	β_3	**-0.7958**	**-28.3404****	
Subsidy & Parking	β_{12}	**0.1273**	**4.6319****	
Subsidy & Congestion	β_{13}	**0.1577**	**5.7228****	
Parking & Congestion	β_{23}	**0.1751**	**6.6372****	
Region (no:0, outside of Seoul:1)	β_{region}	**-0.0814**	**-2.7737****	
Age40 (no:0, 40s:1)	β_{age40}	**0.1534**	**5.6927****	
Income3 (no:0, 5000-7000T won:1)	$\beta_{income3}$	**0.2776**	**10.0632****	L(0) = - 9087.85 L($\widehat{\beta}$) = - 5242.83 ρ^2= 0.423 Number of observations: 494
Income4 (no:0, more than 7,000T won:1)	$\beta_{income4}$	**0.2873**	**10.0667****	
Edu1 (no:0, undergraduate:1)	β_{edu1}	**0.1043**	**4.0632****	
Work2 (no:0, administrative sector:1)	β_{work2}	**-0.3416**	**-12.3576****	
Work3 (no:0, technical sector:1)	β_{work3}	**-0.1827**	**-6.4731****	
Household4 (no:0, family number 4:1)	β_{house4}	**-0.0627**	**-2.4178***	
Child (no:0, having a child:1)	β_{child}	**-0.0664**	**-2.4786***	
Car parking time ratio	$\beta_{C\ parking\ time}$	**-0.1219**	**-4.5016****	
PT waiting time ratio	$\beta_{PT\ waiting\ time}$	**0.1699**	**6.7211****	
Main commute time (no:0, after 8am:1)	$\beta_{commute\ time}$	**0.0931**	**3.4265****	
Support from company (no:0, yes:1)	$\beta_{commute\ support}$	**0.0686**	**2.7700****	
Q2 (environmental awareness)	β_{Q2}	**-0.3319**	**-13.7448****	
Q4 (freedom from regulation)	β_{Q4}	**0.3324**	**12.0849****	
Q5 (importance of convenience)	β_{Q5}	**0.2234**	**8.2650****	
Q7 (importance of cost)	β_{Q7}	**-0.6338**	**-23.9355****	

* The bold figures mean that the coefficient is statistically significant.
* The blue coloured figure means that the order of magnitude of the coefficient is high.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

As shown in **Table 10-13**, since the coefficients related to the interaction effects of MSPs (i.e. β_{12}, β_{13} β_{23}) are statistically significant and the magnitudes of these coefficients represent meaningfully high, it can be interpreted that the interaction effects of MSPs have significant influence on the choice behaviour of travel mode. It indicated the necessity of research on the interaction effect of transport policies.

10.8. Development of a Mixed Logit Model with Additional Covariates

Table 10-14 compares the ρ^2 of the standard logit models with the MLMs (i.e. random coefficient models) with the normal distribution. In terms of the goodness of fit of the estimated models, the ρ^2 values of the standard logit model H1, H2, and H3 are higher than those of the MLM whereas the ρ^2 values of the standard logit model H4 is lower than that of the MLM. These results indicate that the MLM is not always better than the standard logit model in terms of the explanatory power of the model.

Table 10-14. Comparison of rho-squared index of models with additional covariates

Classification	Model H1	Model H2	Model H3	Model H4
Standard logit	0.369	0.328	0.323	0.423
Mixed logit (normal distribution)	0.327	0.250	0.294	0.430

In comparison with **Table 10-2**, **Table 10-5**, **Table 10-9**, **Table 10-11** and **Table 10-15**, the estimated means of the MLM are higher than those of the standard logit models. All the absolute values of the estimated coefficients of the MLM are greater than those of the standard logit models. Most the coefficients are statistically significant in terms of the absolute t-value, with all such values larger than 2.57 and, therefore, significant at the 99% level.

All the mean coefficients and most of the standard deviation coefficients related to the interaction effect of MSPs are statistically significant in the various MLMs with additional covariate variables (i.e. model H1, model H2, model H3, and model H4). In the MLMs with additional covariate variables, most coefficients of the interaction effect of the MSP seem to have substantial explanatory power and preference heterogeneity across individuals. In addition, it indicated that the interaction effect coefficients should be included in the specification of the MLMs.

Since most of the coefficients of standard deviations are statistically significant, it can be interpreted that most coefficients are heterogeneous in the preference of travel mode. In the case of model H1, it can be considered that Q7 (importance of cost) is the most influential factor since the mean coefficient has the highest value (– 67.6367). In addition, since the standard deviation coefficient of the 'Subsidy & Parking & Congestion' variable shows the highest value (4.7767) in model H1, it can be interpreted that this variable is the most flexible factor that has various taste heterogeneity. However, in the case of model H4, since seven standard deviation coefficients are statistically insignificant, these variables do not seem to be heterogeneous in the preference of travel mode.

All in all, some random effect coefficients (standard deviations) and two mean coefficients are statistically insignificant since the absolute t-value is less than 1.65. In addition, since four mean coefficients represent inverse (wrong) signs (see red coloured letters in **Table 10-15**), the development of the MLM does not seem to widely contribute to improving the validity of the model. Therefore, when the MLMs (i.e. model H1, model H2, model H3, and model H4) are compared with the standard logit models which have not only interaction terms but also additional covariates such as attitudinal, socio-economic, and travel factors, the advantages of estimation of the MLMs seem to be reduced.

Table 10-15. Estimation of mixed logit models with normal distribution

Type of model	Coefficient	Beta	Value	t-value	Goodness of fit
Model H1	**ASC**	β_0	**2.2836**	**6.6418****	L(0) = - 9590.38 L(β) = - 6459 ρ^2 = 0.327 Number of observations: 519
	Time (Car) (Mean)	β_4	**-1.4904**	**-401.9446****	
	Random effect (SD)		**2.0607**	**559.2931****	
	Time (PT – Car) (Mean)	β_5	**-0.7370**	**-429.7509****	
	Random effect (SD)		**2.3370**	**631.7019****	
	Cost (PT – Car) (Mean)	β_7	0.9083	105.2629**	
	Random effect (SD)		**2.4222**	**65.8576****	
	Cost (PT) (Mean)	β_6	**-8.5979**	**-582.4389****	
	Random effect (SD)		**1.5387**	**74.3058****	
	PT commuting cost subsidy (Mean)	β_1	**30.8245**	**731.5936****	
	Random effect (SD)		**2.4839**	**77.1103****	
	Additional parking fee (Mean)	β_2	**-34.1856**	**-696.1633****	
	Random effect (SD)		0.1335	1.2320	
	Congestion charge (Mean)	β_3	**-36.5167**	**-711.9687****	
	Random effect (SD)		**3.3829**	**45.7986****	
	Subsidy & Parking (Mean)	β_{12}	**1.4930**	**173.9760****	
	Random effect (SD)		**3.9233**	**482.8720****	
	Subsidy & Congestion (Mean)	β_{13}	**1.5513**	**266.1536****	
	Random effect (SD)		**4.2830**	**761.0144****	
	Parking & Congestion (Mean)	β_{23}	**2.8330**	**241.2755****	
	Random effect (SD)		**4.1864**	**348.7194****	
	Subsidy & Parking & Congestion(Mean)	β_{123}	**-1.2353**	**-510.3632****	
	Random effect (SD)		**4.7767**	**880.6753****	
	Q1 (congestion severity) (Mean)	β_{Q1}	**13.6378**	**200.6629****	
	Random effect (SD)		0.1079	0.5401	
	Q2 (environmental awareness) (Mean)	β_{Q2}	**-41.9010**	**-603.0756****	
	Random effect (SD)		**3.7583**	**29.2821****	

	Q3 (health awareness) (Mean)	β_{Q3}	-6.6873	-144.1397**	
	Random effect (SD)		1.1192	12.1277**	
	Q4 (freedom from regulation) (Mean)	β_{Q4}	25.8248	431.1463**	
	Random effect (SD)		4.4741	37.2034**	
	Q5 (importance of convenience) (Mean)	β_{Q5}	20.2515	264.5958**	
	Random effect (SD)		-0.3337	-2.0409*	
	Q6 (importance of time) (Mean)	β_{Q6}	0.6135	10.4065**	
	Random effect (SD)		-0.9845	-7.2306**	
	Q7 (importance of cost) (Mean)	β_{Q7}	-67.6367	-818.1710**	
	Random effect (SD)		1.2506	14.5217**	
	ASC	β_0	49.1135	52.9998**	
	Time (Car) (Mean)	β_4	-0.6000	-167.0553**	
	Random effect (SD)		-1.1391	-284.4253**	
	Time (PT – Car) (Mean)	β_5	-0.6475	-215.3677**	
	Random effect (SD)		1.3183	287.3939**	
	Cost (PT – Car) (Mean)	β_7	-0.7472	-42.3672**	
	Random effect (SD)		3.2187	51.2147**	
	Cost (PT) (Mean)	β_6	-3.6966	-160.9060**	
	Random effect (SD)		12.3260	361.0209**	
	PT commuting cost subsidy (Mean)	β_1	16.8725	456.2756**	
	Random effect (SD)		12.2280	264.3125**	
	Additional parking fee (Mean)	β_2	-18.8566	-264.0909**	
	Random effect (SD)		1.5737	13.7851**	
	Congestion charge (Mean)	β_3	-20.2958	-274.5128**	
	Random effect (SD)		14.1515	139.4638**	
	Subsidy & Parking (Mean)	β_{12}	0.1777	24.5705**	
	Random effect (SD)		8.1066	539.9316**	
	Subsidy & Congestion (Mean)	β_{13}	0.1427	19.4279**	
	Random effect (SD)		6.1717	457.3985**	
	Parking & Congestion (Mean)	β_{23}	0.7636	37.2041**	
	Random effect (SD)		6.5825	336.0607**	
	Subsidy & Parking & Congestion(Mean)	β_{123}	-0.9215	-364.9529**	L(0) = -9611.87
Model H2	Random effect (SD)		4.1986	561.2131**	L(β) = - 7210.5
	Region (Mean)	β_{region}	0.1330	0.5339	ρ^2 = 0.250
	Random effect (SD)		8.0158	14.8851**	Number of observations: 520
	Gender (Mean)	β_{gender}	35.4090	112.5503**	
	Random effect (SD)		-34.2976	-24.9829**	
	Age 40 (Mean)	β_{age40}	12.5891	39.0110**	
	Random effect (SD)		49.3726	100.7719**	
	Age 50 (Mean)	β_{age50}	4.0784	11.0616**	
	Random effect (SD)		-67.0018	-123.4217**	
	Income 2 (Mean)	$\beta_{income2}$	-5.4907	-11.3752	
	Random effect (SD)		12.0814	15.4383**	
	Income 3 (Mean)	$\beta_{income3}$	-4.4323	-9.1653	
	Random effect (SD)		30.3181	50.9920**	
	Income 4 (Mean)	$\beta_{income4}$	36.1438	75.5326**	
	Random effect (SD)		6.3504	13.9825**	
	Edu1 (Mean)	β_{edu1}	33.0821	85.5139**	
	Random effect (SD)		44.9608	102.3365	
	Edu2 (Mean)	β_{edu2}	18.6123	47.8551**	
	Random effect (SD)		-39.9594	-77.3888**	
	Work1 (Mean)	β_{work1}	0.7388	2.7595**	
	Random effect (SD)		-6.7599	-11.6460**	
	Work2 (Mean)	β_{work2}	-42.9984	-163.9257**	
	Random effect (SD)		19.2431	38.4559**	
	Work3 (Mean)	β_{work3}	-19.8676	-58.6301**	
	Random effect (SD)		24.0510	36.3847**	

	Household2 (Mean)	β_{house2}	-10.9277	-16.6174**	
	Random effect (SD)		15.7572	22.3680	
	Household3 (Mean)	β_{house3}	-3.3280	-5.3580**	
	Random effect (SD)		-27.6264	-61.8182**	
	Household4 (Mean)	β_{house4}	-3.1814	-4.9355**	
	Random effect (SD)		-2.1754	-7.6723**	
	Household5 (Mean)	β_{house5}	-11.4577	-16.3972	
	Random effect (SD)		43.2004	89.0645**	
	Child (Mean)	β_{child}	-9.1852	-41.7962**	
	Random effect (SD)		35.6507	90.1944**	
Model H3	ASC	β_0	58.8964	10.6828**	
	Time (Car) (Mean)	β_4	-0.8817	-24.5950**	
	Random effect (SD)		1.2341	43.8260**	
	Time (PT – Car) (Mean)	β_5	-0.4840	-11.9983**	
	Random effect (SD)		0.1294	9.0661**	
	Cost (PT – Car) (Mean)	β_7	0.4989	2.1293	
	Random effect (SD)		0.1037	0.5952	
	Cost (PT) (Mean)	β_6	-3.9631	-17.5985**	
	Random effect (SD)		2.5611	40.3487**	
	PT commuting cost subsidy (Mean)	β_1	14.1246	82.4711**	L(0) = - 9280.55
	Random effect (SD)		-3.8014	-54.2460**	L(β) = - 6552.2
	Additional parking fee (Mean)	β_2	-16.9672	-44.3374**	ρ^2 = 0.294
	Random effect (SD)		9.5438	22.7157**	Number of
	Congestion charge (Mean)	β_3	-18.8144	-54.9602**	observations: 502
	Random effect (SD)		3.5407	9.8904**	
	Subsidy & Parking (Mean)	β_{12}	0.6035	21.8106**	
	Random effect (SD)		2.6802	63.6176**	
	Subsidy & Congestion (Mean)	β_{13}	0.8191	31.7456**	
	Random effect (SD)		1.4852	44.4307**	
	Parking & Congestion (Mean)	β_{23}	1.4044	20.4309**	
	Random effect (SD)		2.3434	24.8515**	
	Subsidy & Parking & Congestion(Mean)	β_{123}	-0.5881	-53.8123**	
	Random effect (SD)		0.7216	54.1892**	
	Car parking time (%) (Mean)	$\beta_{C\ parking\ time}$	-0.8970	-7.2317**	
	Random effect (SD)		4.5209	46.0733**	
	Car walking time (%) (Mean)	$\beta_{C\ walking\ time}$	-0.4238	-2.1288*	
	Random effect (SD)		2.6760	14.4229**	
	PT waiting time (%) (Mean)	$\beta_{PT\ waiting\ time}$	0.7095	3.8790**	
	Random effect (SD)		2.0919	17.5287**	
	Main departure time (Mean)	$\beta_{commute\ time}$	17.8811	6.1545**	
	Random effect (SD)		5.1335	3.5288**	
	Support from company (Mean)	$\beta_{commute\ support}$	5.2186	1.4860	
	Random effect (SD)		58.1663	11.0820**	
Model H4	ASC	β_0	7.7824	1.5031	
	Time (Car) (Mean)	β_4	-0.3692	-10.0729**	
	Random effect (SD)		0.4672	20.7244**	
	Time (PT – Car) (Mean)	β_5	-0.3764	-12.2939**	
	Random effect (SD)		0.4054	11.6332**	
	Cost (PT) (Mean)	β_6	-3.7408	-19.5734**	
	Random effect (SD)		3.7655	13.9086**	
	PT commuting cost subsidy (Mean)	β_1	14.3740	22.3048**	L(0) = - 9087.85
	Random effect (SD)		-2.7350	-6.3267**	L(β) = - 5180.4
	Additional parking fee (Mean)	β_2	-14.7295	-30.7757**	ρ^2 = 0.430
	Random effect (SD)		3.8178	8.2307**	Number of
	Congestion charge (Mean)	β_3	-15.9916	-31.2344**	obserbations: 494
	Random effect (SD)		1.4009	4.2793**	
	Subsidy & Parking (Mean)	β_{12}	0.7424	5.4292**	

	Random effect (SD)		0.0384	0.2589	
	Subsidy & Congestion (Mean)	β_{13}	**0.7988**	**7.0219****	
	Random effect (SD)		-0.0687	-0.5944	
	Parking & Congestion (Mean)	β_{23}	**0.9767**	**12.7929****	
	Random effect (SD)		**1.0194**	**13.1638****	
	Region (Mean)	β_{gender}	-2.8810	-1.5898	
	Random effect (SD)		2.7585	1.2349	
	Age 40 (Mean)	β_{age40}	**10.9361**	**6.3049****	
	Random effect (SD)		-0.0941	-0.0474	
	Income 3 (Mean)	$\beta_{income3}$	**16.4894**	**8.0729****	
	Random effect (SD)		**-25.2938**	**-12.0273****	
	Income 4 (Mean)	$\beta_{income4}$	**22.3281**	**10.6192****	
	Random effect (SD)		-1.8864	-0.7480	
	Edu1 (Mean)	β_{edu1}	-0.0919	-0.0537	
	Random effect (SD)		**39.8529**	**18.4879****	
	Work2 (Mean)	β_{work2}	**-24.4603**	**-12.6422****	
	Random effect (SD)		**-11.5076**	**-5.9135****	
	Work3 (Mean)	β_{work3}	**-17.1621**	**-7.0043****	
	Random effect (SD)		**8.2752**	**2.5008***	
	Household4 (Mean)	β_{house4}	**-4.5550**	**-2.8735****	
	Random effect (SD)		**4.2490**	**2.5341***	
	Child (Mean)	β_{child}	**-6.7106**	**-3.9293****	
	Random effect (SD)		**20.7730**	**11.8415****	
	Car parking time (%) (Mean)	$\beta_{C\ parking\ time}$	**-0.6091**	**-5.1473****	
	Random effect (SD)		**0.4769**	**4.2304****	
	PT waiting time (%) (Mean)	$\beta_{PT\ waiting\ time}$	**0.7968**	**7.1118****	
	Random effect (SD)		**0.4458**	**5.3151****	
	Main departure time (Mean)	$\beta_{commute\ time}$	**5.3636**	**3.0421****	
	Random effect (SD)		**3.1169**	**2.0636***	
	Commute support from company (Mean)	$\beta_{commute\ support}$	**5.7968**	**2.7929****	
	Random effect (SD)		-0.2223	-0.0697	
	Q2 (environmental awareness) (Mean)	β_{Q2}	**-15.1576**	**-13.1985****	
	Random effect (SD)		**-1.6647**	**-2.3939***	
	Q4 (freedom from regulation) (Mean)	β_{Q4}	**10.9768**	**11.6302****	
	Random effect (SD)		0.8033	1.4548	
	Q5 (importance of convenience) (Mean)	β_{Q5}	**10.5322**	**8.3510****	
	Random effect (SD)		**3.3773**	**4.1739****	
	Q7 (importance of cost) (Mean)	β_{Q7}	**-27.2084**	**-19.2188****	
	Random effect (SD)		**1.8495**	**3.1998****	

* The red coloured figures denote that the variable has an inverse sign.
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

10.9. Summary

In this study, the main subject is to understand what factors affect the choice of travel mode. To this end, models with additional covariates are developed to investigate the most influential explanatory factors affecting travel mode choice. Since a wide variety of additional covariates can be put into a logit model, it is possible to investigate what factors affect the choice of travel mode. To gauge the relative influence of explanatory variables, the standardization methods are also used.

Let's review the development results of diverse covariate models. First and foremost, the ρ^2 values of model H1 (0.369), H2 (0.328), H3 (0.323), and H4 (0.423) are higher than the default model E1 (0.303). This result illustrates the validity of the covariate models. Second of all, a utility function model with attitudinal factors is created as in model H1 in order to investigate the influence of attitudinal factors. Since the coefficient value (– 0.6602) of β_{Q7} is the highest out of seven attitudinal factors in the standardized model H1, it can be inferred that there is the strongest reverse relationship between 'the consciousness of the importance of cost factor' and 'the utility of car use'. Third, a utility function model with socio-economic factors is developed as model H2. Since the coefficient value (0.7822) of $\beta_{income4}$ is the highest out of eight socio-economic factors in the standardized model H2, it can be inferred that there is the strongest affirmative relationship between 'people whose household income are more than 7,000,000 won (about £3,889)' and 'the utility of car use'. Fourth, a utility function model with travel factors is constructed as model H3. Since the coefficient (0.3398) of $\beta_{commute\ time}$ is the highest out of five travel factors in the standardized model H3, it can be inferred that there is the strongest positive relationship between 'people whose main commute time is after 8 a.m.' and 'the utility of car use'. Fifth, a synergistic covariate model with all the factors such as attitudinal, socio-economic and travel factors is developed as model H4 in order to understand the influence of all the explanatory variables. In the standardized model H4, the coefficient value of congestion charges is – 0.7958, additional parking fees – 0.5690, and PT commuting cost subsidies 0.5862. It indicates that the 'alternative-specific variables' (level of MSP) have the most powerful influence on mode choice decision. An interesting finding is that attitudinal factors seem to be the next most effective explanatory variables. The consciousness of the importance of cost (– 0.6338), the environmental protection (– 0.3319), and the freedom of regulation (0.3324) shows high coefficient values. This result indicates the necessity of introduction of informative measures such as environmental awareness campaign as an ancillary/secondary policy.

In addition, to reflect individual's taste heterogeneity into the models, the MLMs with additional covariates are also developed. In comparison with the ρ^2 value in the MLMs and the standard logit models, the MLMs do not seem to always be better than the standard logit models. In addition, since some coefficients in the MLMs have wrong (inverse) signs and are statistically insignificant, the validity of the calibration of the MLMs seems to be low. That is, in the case of the MLMs with additional covariates, the advantage of the development of the MLM seems to be reduced.

Chapter 11. Budget Availability and Political Acceptability

11.1. Introduction

The purpose of this chapter is to compare the magnitude of the revenues arising from the MSPs and expenditure for MSPs and to review political acceptability. This chapter consists of four more sections. Section 11.2 arranges the research background of revenue and expenditure of the MSPs. Section 11.3 calculates annual expenditure of the PT commuting cost subsidies as well as annual revenue from additional parking fees and congestion charges. Section 11.4 investigates the use of the revenue in terms of productive efficiency, horizontal equity, vertical equity, and political acceptability. Section 11.5 deals with the political acceptability of the MSPs and policy packaging.

11.2. Research Background

Nowadays, most countries are suffering the deficit of government finance. Therefore, it would be desirable that the revenue from transportation sector can cover all the cost such as the provision of transport and operational cost because the extra revenue results eventually in the reduction of the general tax level. In particular, if more revenue from transportation sector can reduce the general taxes such as labour tax or property tax, it may bring efficiency gains of society. Thus, the obtainment of the revenue from the transportation policy may be main issues in the pragmatic perspective.

Since effective modal shifts require a whole set of supportive pricing policies, regulations, and investments, finding and securing the funding for transport investments or transport policy can be a key issue in policy implementation. For example, the combination of congestion charges and the investment on PT may create an effective modal shift from car to PT and eventually significant social benefits. Therefore, although maximizing the revenue is not always a priority among the policy's objectives, maximizing the revenue may be one of the key issues in practice.

In general, the amount of revenue derived from transport user charges depends on many factors such as the level of charges, scope and flexibility of the pricing scheme, competitiveness of factor markets, political acceptability, and trust on the effectiveness of policy. Additionally, how revenues will be distributed may be as important as the acceptance of the levying charging itself sometimes. In general, although getting more revenue is needed, the situation is strictly limited.

Meanwhile, all the policies are strictly constrained by the available resources such as money, manpower and knowledge. Considering real limitations, the more practical, feasible, and acceptable approach is to reflect the resource constraints of transport policy. The financial cost resources, in most cases, may be a barrier to the successful implementation of a policy. In particular, PT commuting cost subsidies, as a means of substantially increasing benefits, requires substantial revenue support. That is, the effect of PT commuting cost subsidies can heavily depend on budget availability. In reality, the real introduction of the MSP requires the consideration of both revenue from the MSP and expenditure of the MSP. The introduction of new pricing policy instruments requires how to get the monetary resource for the implementation of the MSP and what to do with new revenues of the MSP. In general, the government used to allocate revenues in terms of the equity and the political acceptability. In this chapter, the magnitude of revenue from the MSP and expenditure on the MSP is estimated to judge the potential of the introduction of a new MSP.

11.3. Revenues from a Policy and Expenditures for a Policy

11.3.1. Additional parking fee

As shown in **Table 11-1**, the total parking lot is 640,871 in the Gangnam area. However, parking lots for residents (290,674) should be excluded in this research. In addition, the classification of general building sector includes a shopping centre, department store and so on. Therefore, 70% of parking lots in general buildings (217,837 = 311,196*7/10) are supposed to be possible target parking lot. To sum up, the number of possible designated parking lot spaces to apply additional parking fees will be 256,399 (= 16,744 + 6,790 + 15,028 + 217,837).

Table 11-1. Present condition of parking lot in the Gangnam area

Classification	Total			On-street parking lot	Off-street parking lot		Attached to building	
	Sum	Public	Private		Public	Private	Resident	General
Seocho-Gu	271,917	8,561	262,917	**6,219**	**2,342**	**9,504**	127,301	**126,112**
Gangnam-Gu	368,954	14,973	353,981	**10,525**	**4,448**	**5,524**	163,373	**185,084**
Total	640,871	23,534	616,898	**16,744**	**6,790**	**15,028**	290,674	**311,196**

* Source: National statistics (Korean Government), 2013.

Table 11-2 shows the estimated market share rate of the car use and modal shift rate of the car use based on the current state in respect to the change of level of MSPs in model B2. In addition, as shown in **Table 11-3**, as the level of additional parking fees goes up, the number of workers who use the parking lots will decrease because the demand of the parking lot will be declined.

Table 11-2. Estimated market share rate of car use and the modal shift rate of car use based on the current state with respect to the change of level of MSPs in model B2 (unit: %)

Type of Model	Level of policy	PT subsidy	Parking fee	Congestion charge	Subsidy& Parking	Subsidy& Congestion	Parking& Congestion	Three MSPs
Model B2	₩0	58.28	58.28	58.28	58.28	58.28	58.28	58.28
	₩1,000	53.31 (-8.53)	50.55 (-13.26)	50.22 (-13.83)	45.99 (-21.09)	45.67 (-21.64)	43 (-26.22)	39.03 (-33.03)
	₩2,000	48.28 (-17.16)	42.8 (-26.56)	42.15 (-27.68)	35.01 (-39.93)	34.44 (-40.91)	29.83 (-48.82)	24.82 (-57.41)
	₩3,000	43.28 (-25.74)	35.38 (-39.29)	34.48 (-40.84)	26.13 (-55.16)	25.42 (-56.38)	20 (-65.68)	16.06 (-72.44)
	₩4,000	38.42 (-34.08)	28.61 (-50.91)	27.55 (-52.73)	19.42 (-66.68)	18.68 (-67.95)	13.3 (-77.18)	11.1 (-80.95)
	₩5,000	33.77 (-42.06)	22.68 (-61.08)	21.54 (-63.04)	14.57 (-75.00)	13.85 (-76.24)	8.94 (-84.66)	8.39 (-85.60)
	₩6,000	29.42 (-49.52)	17.68 (-69.66)	16.55 (-71.60)	11.13 (-80.90)	10.47 (-82.04)	6.16 (-89.43)	7.03 (-87.94)

* The values in parenthesis ( ) means the change rate of modal shift from car to PT according to the change of level of MSP based on the current state.

$\left(\frac{\textit{market share after the implementation of the MSP \%}}{\textit{market share before the impelemtatin of the MSP \%}} - 1\right) \times 100\%$

Table 11-3. Number of parking lot users in the implementation of additional parking fees in the Gangnam area

Classification	No of lot	₩1,000	₩2,000	₩3,000	₩4,000	₩5,000	₩6,000
Modal shift rate		-13.26	-26.56	-39.29	-50.91	-61.08	-69.66
Seocho-Gu	106,343	92,242	80,011	69,401	60,199	52,216	45,293
Gangnam-Gu	150,056	130,158	112,899	97,929	84,944	73,680	63,910
Total	**256,399**	222,401	192,910	167,330	145,142	125,897	109,203

Table 11-4. The estimated annual revenue of additional parking fees in the Gangnam area (unit: won)

Classification	₩1,000	₩2,000	₩3,000	₩4,000	₩5,000	₩6,000
Seocho -Gu	23,245,050,820 (£12,913,917)	40,325,514,163 (£22,403,063)	52,467,526,478 (£29,148,626)	60,680,443,289 (£33,711,357)	65,792,770,636 (£36,551,539)	68,482,379,100 (£38,045,766)
Gangnam -Gu	32,799,917,032 (£18,222,176)	56,901,296,067 (£31,611,831)	74,034,276,313 (£41,130,154)	85,623,108,365 (£47,568,394)	92,836,855,244 (£51,576,031)	96,632,025,887 (£53,684,459)
Total	56,044,967,852 (£31,136,093)	97,226,810,230 (£54,014,895)	126,501,802,790 (£70,278,779)	146,303,551,654 (£81,279,751)	158,629,625,880 (£88,127,570)	**165,114,404,986 (£91,730,225)**

* Revenue = the number of parking lots × month (12) × average monthly working day (21) × charge level

In the analysis, the basic assumption is that each parking space can levy additional parking fees on users only once in a single day. **Table 11-4** shows that as the level of additional parking fees goes up, the revenue increases. The revenues from additional parking fees can be calculated to be maximum 165 billion won (about £92 million). However, in terms of the revenue, this figure must be overestimated since this revenue includes the private sector. In general, since parking fee is a reward from the use of land, the parking fee of private parking lots belongs to the property owner or manager. Although the policy of additional parking fees may be implemented by governmental instruction, it is impossible to make the additional parking fees stemming from the private parking lot the source of revenue in the governmental sector. The improper expropriation for public use must be encroachment of private property right. Therefore, this problem may be delicate political issues. Considering these situations, more practical and acceptable estimation of revenue is the exclusion of the revenue of private sector. As shown in **Table 11-5**, the total number of public parking lots in the Gangnam is 23,534. In addition, **Table 11-5** shows the change of the number of public parking lots in accordance with the level of additional parking fees.

Table 11-5. The number of public parking lots in which the commuter uses in the implementation of additional parking fees in the Gangnam area

Classification	No. of lot	₩1,000	₩2,000	₩3,000	₩4,000	₩5,000	₩6,000
Modal shift rate		-13.26	-26.56	-39.29	-50.91	-61.08	-69.66
Seocho-Gu	8,561	7,426	6,441	5,587	4,846	4,204	3,646
Gangnam-Gu	14,973	12,988	11,265	9,772	8,476	7,352	6,377
Total	**23,534**	20,413	17,707	15,359	13,322	11,556	10,023

As shown in **Table 11-6**, the estimated annual revenue of additional parking fees from public parking lots is maximum only 15 billion won (about £8 million). The amount of revenue is too small to use as a new revenue source.

Table 11-6. The estimated annual revenue of additional parking fees from public parking lot in the Gangnam area (unit: won)

Classification	₩1,000	₩2,000	₩3,000	₩4,000	₩5,000	₩6,000
Seocho -Gu	1,871,304,473 (£1,039,614)	3,246,338,999 (£1,803,522)	4,223,811,672 (£2,346,562)	4,884,978,993 (£2,713,877)	5,296,538,473 (£2,942,521)	5,513,060,965 (£3,062,812)
Gangnam -Gu	3,272,870,210 (£1,818,261)	5,677,775,241 (£3,154,320)	7,387,353,366 (£4,104,085)	8,543,720,413 (£4,746,511)	9,263,528,858 (£5,146,405)	9,642,221,917 (£5,356,790)
Total	5,144,174,683 (£2,857,875)	8,924,114,240 (£4,957,841)	11,611,165,038 (£6,450,647)	13,428,699,406 (£7,460,389)	14,560,067,330 (£8,088,926)	**15,155,282,883** (**£8,419,602**)

11.3.2. Congestion charge

In terms of theoretical perspective, first-best pricing (i.e. Pigouvian marginal external cost pricing) is an acceptable solution of obviating negative externalities. However, first-best pricing requires three assumptions. First, regulators must build perfectly differentiated taxes for all road users and on all links of the network. Second, first-best conditions prevail throughout the economic environment to which the transport system belongs. Third, every participant has perfect information on traffic conditions and tolls (Tillema et al., 2013). However, the assumption is difficult to be satisfied in a real situation. Therefore, secondary schemes are needed to circumvent the difficulties from the first-best solutions. Thus, price measures can vary according to the intensity, type, and coverage of the policy. As shown in **Table 11-7**, the total volume of inflow traffic is 2,600,716 per day, and the total volume of inner pass traffic is 1,190,605 per day. In this study, except for an outflow traffic, the sum of inflow and inner pass traffic is regarded as the number of target transport mode. This number is the total sum including every type of transport mode. Thus, since the target transport mode of congestion charging is the private car, the number of the target transport mode should be multiplied by the market share rate of the car (33.6%) in **Table 11-8**.

Table 11-7. Total volume of traffic in the Gangnam area (unit: traffic volume/day as of 2011)

Classification	Inflow	Outflow	Inner pass	Sum
Seocho-Gu	1,029,080	1,014,440	431,288	2,475,808
Gangnam-Gu	1,631,636	1,584,184	759,317	3,975,137
Total	**2,660,716**	2,598,624	**1,190,605**	6,450,945

* Source: Gangnam local government, 2012, 2020 Gangnam medium and long-term transport plan.

Table 11-8. The market share of the transport mode (unit: %, as of 2011)

Classification	Car	Bus	Subway	Taxi	Other	Sum
Gangnam-Gu	**33.6**	23.2	32.4	7.6	3.1	100
Seoul (average)	30.6	32.3	24.8	6.7	5.6	100

* Source: Gangnam local government, 2012, 2020 Gangnam medium and long-term transport plan.

Table 11-9 represents that the number of target car is changed in accordance with the toll level since the market share of the car (transport demand) is changed in accordance with the toll level.

Table 11-9. Volume of traffic in implementation of congestion charges in the Gangnam area

Classification	Number of target car	₩1,000	₩2,000	₩3,000	₩4,000	₩5,000	₩6,000
Modal shift rate		-13.83	-27.68	-40.84	-52.73	-63.04	-71.60
Seocho-Gu	343,479	**295,976****	**248,415*****	203,211	162,369	126,948	97,539
Gangnam-Gu	562,352	484,580	406,711	332,702	265,834	207,843	159,693
Total	**905,831***	780,556	655,126	535,914	428,202	334,791	257,232

* Total number of target cars (**905,831***) = 3,851,321 [=2,660,716+1,190,605] × (**33.6**/100) [=number of target transport mode] × (7/10) [the supposed value for reduced ratio of traffic volume considering operational time of congestion charges]

* **295,976**** = 343,479 – 343,479 × (13.83/100), **248,415***** = 343,479 – 343,479 × (27.68/100)

Table 11-10 shows that despite the decrease in the car use, the revenue increases up to the level of 4,000 won. When the level of the toll is 4,000 won, the revenue is maximized. The annual revenue from congestion charges is calculated to be more than 431 billion won (about £240 million) for 4,000 won charging scenario. In reality, the level of congestion charges might mainly depend on the level of the externality (traffic congestion) largely due to the political acceptability. In addition, the use of revenue can be a contributory factor for the introduction of congestion charges.

Table 11-10. The estimated annual revenue from congestion charges in the Gangnam area (unit: won)

Classification	₩1,000	₩2,000	₩3,000	₩4,000	₩5,000	₩6,000
Seocho -Gu	74,586,056,017 (£41,436,698)	125,201,205,142 (£69,556,225)	153,627,670,936 (£85,348,706)	163,667,530,328 (£90,926,406)	159,954,564,577 (£88,863,647)	147,478,999,651 (£81,932,778)
Gangnam -Gu	122,114,138,553 (£67,841,188)	204,982,514,537 (£113,879,175)	251,523,028,513 (£139,735,016)	267,960,535,017 (£148,866,964)	261,881,575,511 (£145,489,764)	241,456,271,572 (£134,142,373)
Total	196,700,194,570 (£109,277,886)	330,183,719,679 (£183,435,400)	405,150,699,449 (£225,083,722)	**431,628,065,345 (£239,793,370)**	421,836,140,088 (£234,353,411)	388,935,271,223 (£216,075,151)

11.3.3. Public transport commuting cost subsidy

As shown in **Table 11-11**, the total number of workers in the Gangnam area is 988,168. Although the expenditure of PT commuting cost subsidies depends on the application scope to the size of the company, the analysis is supposed that every worker is covered. In addition, as indicated in **Table 11-12**, 41.72% of workers use PT at present. However, as shown in **Table 11-13**, as the level of subsidy goes up, the number of workers who use PT will increase.

Table 11-11. Number of workers in the Gangnam area (2012)

Classification	Total	1-4 persons	5-9 persons	10-49 persons	50-99 persons	100-499 persons	500-999 persons	1,000 persons+
Seocho-Gu	376,962	61,322	42,578	86,845	34,532	72,533	33,408	45,540
Gangnam-Gu	611,206	87,916	72,857	147,402	60,991	144,252	42,231	55,557
Total	**988,168**	149,238	115,435	234,247	95,523	216,785	75,639	101,097

* Source: Seoul city statistics, 2013.

Table 11-12. The estimated market share rate of PT and modal shift rate of PT based on the current state with respect to the change of level of MSPs in model B2 (unit: %)

Type of Model	Level of policy	Subsidy	Parking	Congestion	Subsidy& parking	Subsidy& Congestion	Parking& Congestion	Subsidy& Parking& Congestion
Model B2	₩ 0	41.72	41.72	41.72	41.72	41.72	41.72	41.72
	₩1,000	46.69 (11.91)	49.45 (18.53)	49.78 (19.32)	54.01 (29.46)	54.33 (30.23)	57 (36.63)	60.97 (46.14)
	₩2,000	51.72 (23.97)	57.2 (37.10)	57.85 (38.66)	64.99 (55.78)	65.56 (57.14)	70.17 (68.19)	75.18 (80.20)
	₩3,000	56.72 (35.95)	64.62 (54.89)	65.52 (57.05)	73.87 (77.06)	74.58 (78.76)	80 (91.75)	83.94 (101.20)
	₩4,000	61.58 (47.60)	71.39 (71.12)	72.45 (73.66)	80.58 (93.14)	81.32 (94.92)	86.7 (107.81)	88.9 (113.09)
	₩5,000	66.23 (58.75)	77.32 (85.33)	78.46 (88.06)	85.43 (104.77)	86.15 (106.50)	91.06 (118.26)	91.61 (119.58)
	₩6,000	70.58 (69.18)	82.32 (97.32)	83.45 (100.02)	88.87 (113.02)	89.53 (114.60)	93.84 (124.93)	92.97 (122.84)

Table 11-13. Expected population of receiving PT commuting cost subsidies in the Gangnam area

Classification	Population	₩1,000	₩2,000	₩3,000	₩4,000	₩5,000	₩6,000
Market share of PT	-	46.69	51.72	56.72	61.58	66.23	70.58
Seocho-Gu	376,962	176,004	194,965	213,813	232,133	249,662	266,060
Gangnam-Gu	611,206	285,372	316,116	346,676	376,381	404,802	431,389
Total	988,168	461,376*	511,080	560,489	608,514	654,464	697,449

* 461,376* = 988,168 × (**46.69**/100)

Table 11-14 shows that the magnitude of the expenditure is changed in accordance with the support level. As shown in **Table 11-14**, if the level of subsidy is 4,000 won, the estimated annual expenditure would be 613 billion won (about £341 million). However, the distribution of expenditure might be divided into an employer, local government, and central government. In addition, the magnitude of governmental expenditure might largely depend on the types of subsidy scheme such as a full tax deduction, a partial tax deduction, a differential deduction based on the income level and so on. Therefore, the real expenditure of the government sector can be reduced by the type of subsidy scheme.

Table 11-14. Estimated expenditure of PT commuting cost subsidies in the Gangnam area (unit: won)

Classification	₩1,000	₩2,000	₩3,000	₩4,000	₩5,000	₩6,000
Seocho -Gu	44,352,896,566 (£24,640,498)	98,262,232,186 (£54,590,129)	161,642,511,878 (£89,801,395)	233,990,265,197 (£129,994,592)	314,574,035,076 (£174,763,353)	402,282,386,755 (£223,490,215)
Gangnam -Gu	71,913,764,513 (£39,952,091)	159,322,334,573 (£88,512,408)	262,087,088,659 (£145,603,938)	379,391,700,038 (£210,773,167)	510,050,184,588 (£283,361,214)	652,260,462,538 (£362366924)
Total	116,266,661,078 (£64,592,589)	25,758,4566,758 (£143,102,537)	423,729,600,538 (£235,405,334)	**613,381,965,235** (**£340,767,758**)	824,624,219,664 (£458,124,566)	**1,054,542,849,293** (**£585,857,138**)

* Expenditure = the number of workers × month (12) × average monthly working day (21) × support level.

The PT commuting cost subsidies need a substantial budget. However, if this policy has a very low effectiveness of modal shift, the difficulty of securing a budget will be aggravated due to the lack of political acceptability. In this case, it may be considered as a government wasting money. In particular, since PT users at present will become free riders inevitably, this policy can become very expensive. Consequently, the efficiency problem of governmental expenditure in the implementation of the PT commuting cost subsidies may be called into question.

11.4. The Use of the Revenue

In a constrained fiscal environment, revenue can be used as general revenue for general budget purposes or as earmarked revenue for overarching transport projects. To use the revenue from the MSP efficiently and effectively, a lot of considerations are needed, including productive efficiency, horizontal equity, vertical equity, and political acceptability (Monsalve, 2013).

Goodwin (1989) suggested that “a third of the toll revenue be used to improve the effectiveness of public transport, that a third be used for new road infrastructure and maintenance, and that a third be used for general city funds” (Mirabel and Reymond, 2011). Small (1992) investigated the possibilities for designing a package of revenue uses. He also proposed that redistribution of the toll revenue require creating a general consensus across several key interest group as well as a wide range of people by lowering taxes, funding new highways, improving transit, and upgrading business centres. Hau (1992) suggested that toll payer should be reimbursed through not only public service improvements but also reduced transportation rates and taxes. He proposed that earmarking can benefit everyone financially. Litman (2011) proposed that toll revenues should help society as a whole, not only road users. He argues that toll revenues should be used to benefit society and should not be refunded proportionately to road users. Parrry and Bento (2001) advocated that the overall welfare gain would increase and labour supply would be stimulated if congestion tax revenues were used to cut labour taxes. King et al. (2007) showed that toll revenue should be allocated towards city budgets for various environmental and public health costs in order to ensure the feasibility of the policy (Mirabel and Reymond, 2011).

11.4.1. Productive efficiency

Productive efficiency is related to the use of resources to maximize the production of good and services. Productive efficiency occurs when the economy uses all of its resources efficiently. That is, it occurs when the highest possible output of one good at the lowest resource input (cost) is produced. From the microeconomic perspectives, productive efficiency can be created at the intersection where marginal cost equals average cost.

In the transportation sector, traffic congestion is representative of negative externalities. An MSP is one of the various ways of internalising externalities such as travel delays, air pollutions, noise, and road accidents. In terms of social welfare, the efficiency of MSP is heavily influenced by the reduction of traffic congestion. The reduction of traffic congestion leads directly to the decrease of time losses wasting on the road and environmental damages such as emission and noise. In addition, the modal shift from car to PT results in the reduction of surplus fuel consumption derived from the use of cars.

The efficiency gains created by transport policy may be a public good that is insufficiently utilized in the transportation sector. In general, since marginal social cost exceeds the marginal private cost in case that external diseconomy exists, demand for the use of the road is too high. Internalising external social cost by increasing the price of the car use can be an economic solution for narrowing the discrepancy between marginal social costs and marginal private cost in order to maximise social net benefit and eliminate negative economic effects (external diseconomy). Since economic efficiency is related to the use of social resources to achieve the maximum social benefit, the appropriate use of social resources through transport policy can increase efficiency by reducing traffic congestion (Litman, 2011). The revenue from internalising the external social cost can be also used for the provision of public goods (Givoni, 2014b) to help enhance economic efficiency.

To improve market efficiency by reducing the external social cost, the improvement of PT facilities or services and the provision of incentives to change people’s travel behaviour can be desirable policies. Almost all of the transportation policies and projects including the MSPs tend to focus on the efforts to reduce marginal social cost. In this case, the reduction of traffic congestion depends on the type of MSP scheme and the level of MSP. That is, the PT commuting cost subsidies can reduce marginal social cost as a pull measure whereas the additional parking fees and congestion charges can also decrease marginal social cost as push measures. For example, if the intensity (level) of push measures as Pigouvian toll tax is equal to the marginal external congestion cost (Hau, 1992), productive efficiency may be achievable. In addition, if the minimum budget input into the PT commuting cost subsidies produces the maximum modal shift effects from car to PT, productive efficiency would be satisfied.

11.4.2. Horizontal equity and vertical equity

There are controversial debates about fair or equitable use of revenue from congestion charges in the theoretical viewpoint. Since parking fees may be regarded as the reward for parking lot usage, the use of revenue from parking fees seems most commonly used to pay for transport projects or property owners. However, for congestion charges, there are arguments about two concepts of equity: horizontal equity and vertical equity (Litman, 2011).

Horizontal equity is associated with the idea that "people with a similar ability to pay taxes should pay the same or similar amounts" (Litman, 2011). Thus, the revenue from MSP should be devoted to road improvement or to providing other benefits to people who pay the charge. However, since road use imposes an external cost on other people by inducing traffic congestion, the revenue should be returned to car users only after external cost is compensated (Litman, 2011). In general, since the revenue from MSP is less than the external cost, the proposition that the revenue benefit for only road user cannot be accepted.

Vertical equity refers to the idea that "people with an increased ability to pay taxes should pay more, as the distribution of costs and benefits should reflect people's needs" (Monsalve, 2013). If a policy favours disadvantaged groups such as the poor, senior and the disabled people, the policy is equitable. While MSP favouring economically or socially disadvantaged groups is called progressive, MSP burdening disadvantaged groups is called regressive. Thus, congestion charges are often considered inequitable since it imposes larger burdens on the poor. Vertical equity is often measured regarding income. However, an income-focused approach can be a drawback since people with the same income often have different needs and abilities. Nevertheless, income analysis provides useful insights and information. However, there are arguments against the concept of vertical equity. Some researchers argue that since the low-income group drives much less than the high-income group (Monsalve, 2013), compensation for the low-income group is not needed. In conclusion, although horizontal equity and vertical equity are a meaningful and useful concept in the theoretical aspect, it is not ironbound principle, just a consideration.

In this study, since the estimated external annual cost from traffic congestion in South Korea as of 2007 is 25,862 billion won, the revenue from MSP seems to be very much smaller than its cost (Jang et al., 2009). In addition, in terms of the portion (π_h) of the CVPP to the average income of each income group, the PT commuting cost subsidies are progressive while additional parking fees and congestion charges are regressive. However, in aspect of the absolute value of the CVPP, the CVPP of congestion charges and the CVPP of additional parking fees for the low income group is lower than that of the high income group, whereas the CVPP of the PT commuting cost subsidies for the low income group is higher than that of the high income group. It seems to indicate that since the low income group tends to use PT more frequently than the other groups, their consumer benefits from the PT commuting cost subsidies are greater than the higher income group. In addition, since the high income group drives more than the low income groups, their consumer losses from congestion charges or additional parking fees are bigger than the low income group.

11.4.3. Political acceptability of revenue usage

The idea that the revenue should be dedicated to road improvement for road users is politically feasible, but some analyses indicate that tax reductions or financial rebates benefit the largest number of citizens and may be more politically popular (Litman, 2002; Parry and Bento, 2001). Revenue neutrality argues that congestion charging should be compensated through reduced taxes or cash rebates so that road users are no worse off. However, this argument is criticized on some grounds. There are doubts about that revenue neutrality can contribute to the enhancement of equity. For example, if the revenue is used to reduce taxes, the overall outcome can be regressive. Conversely, if the revenue is used to finance PT projects, the overall impact can be progressive (Monsalve, 2013). In addition, since congestion charges can obtain political support by using the revenue for the improvement of PT facilities or services, revenue neutrality may face rather political unacceptability. Under financial constraints, finding revenues to finance investments necessary for the modal shift is also needed. Thus, the revenues can be earmarked for specific purposes such as new PT investments, improvement of existing infrastructures to effectively increase the market share of PT (Monsalve, 2013). That is, aside from investment for PT facility, the revenue from road user charges can also be used to improve service of PT and make PT more attractive to commuters. In the case of London and Stockholm’s congestion charge, the revenues were used to improve and expand PT (Monsalve, 2013). Furthermore, in the case of the heavy-vehicle fee in Switzerland, 2/3 of revenues were used to finance two specified railway tunnels. Meanwhile, many people worry that the money from revenues will vanish into 'the black hole' federal or municipal budget (Schlag, 1997). For these reasons, many politicians welcome the use of revenues to finance new investments in the transport sector. Many studies have found that earmarking toll revenues can enhance public acceptance and gain political acceptability.

However, earmarking of revenues is unlikely to be optimal for economic efficiency, and many economists would prefer that revenues were channelled to the general public budget. That is, earmarking, meaning the practice of directing funds to designated recipients for specific purposes (Brach and Wachs, 2005), may have a loss of economic efficiency. Efficiency loss can be derived from inflexibility built in by the hypothecation and lack of incentives for the recipients to use the budgets optimally (Monsalve, 2013). In addition, earmarking can damage budget control because priorities used to change over time. However, in the theoretical viewpoint, the benefits of earmarking for specific purposes should somewhat outweigh a reduced economic efficiency. Brett and Keen (2000) explain why earmarking still exists, despite its intrinsic inefficiency for two types of reason. First, people want to minimise the losses. Although earmarking is not optimal resource distribution, this method can at least prevent wasting revenues for squandering and futile other projects. In addition, since earmarking can make substantial social gains, distorting taxes may be diminished. Second, the level of other taxes can be reduced because the use of revenues from road user charges does not increase public expenditure (Proost et al., 2004).

All in all, earmarking to invest in transport projects can be a compromise in order to secure the implementation of project, but the effects in the longer term can prove counterproductive, as the earmarking tends to create new traffic. However, earmarking the toll revenue can enhance political acceptability (Ison, 2000; Thorpe et al., 2000; King et al., 2007). In addition, an explicit package of tolls and revenue usages is needed to enhance political feasibility (Small, 1983). In reality, most road pricing schemes involve a high degree of earmarking of revenues (Iso and Rye, 2008). Therefore, the concept of earmarking offers insight and a clue on the effective combination of transportation policies.

11.5. Political Acceptability of Modal Shift Policies

11.5.1. Barrier to the implementation of policy

Although acceptability is often closely related to the distributional effect of disincentive MSP, a lack of support for the policy objective may be a cause of low acceptability. Political acceptability is often affected by public opposition. In general, a lack of acceptability may arise from two sources.

Firstly, in many cases the process of policy has been considered illegitimate because of a lack of transparency, accountability and inclusivity (OPTIC, 2011b). It is a problem of the process, rather than the outcome in terms of the types of interventions. An unclear legal basis and a lack of communication of expected benefits can lead to decreasing transparency and avoidable resistance. Barriers are often related to negative attitude, lack of acceptance, and resistance to a certain policy measure among the public (OPTIC, 2011a). The basic reason of barriers may be traced back to various factors, such as deeply embedded social norms, and low trust of experts or policymakers (OPTIC, 2011a). The discrepancy between anticipation and reality may be caused by lack of knowledge and inadequate communication and information. Therefore, providing clear information about the objective and expected consequences of policy may increase people's awareness and positive attitudes. In addition, positive and active communication, organizational responsibility, and transparency enhancement of policy process would be helpful for enhancing acceptability.

Second, a lack of acceptability may arise from the anticipation of major stakeholders that the MSP includes measures contradictory to their interests (OPTIC, 2011b). In many cases, stakeholder opposition against the MSP may occur since the implementation of policy is at odds with their economic interests. Public acceptance heavily depends on equity effects of MSP, the level of charges, and the use of revenues. When it comes to a solution of inequitable problems derived from negative economic policy intervention, compensating measures for groups whose welfare will decrease can be used as one solution method (Johansson et al. 2001). In terms of the level of charges, at the initial stage of negative economic intervention, low starting levels are needed and then the charges can be increased over time (Güller, 2002). This method can be another solution for improving acceptability.

Traffic congestion is a major problem in both developed and developing countries. Although the traffic situations of big cities in developed countries are different according to the extent of automobile dependence and population density, transportation systems are relatively well organized and well equipped compared to developing countries. On the other hand, major cities in developing countries such as Bangkok, Bombay, Jakarta, Manila, Seoul, Mexico City, Rio de Janeiro, and Sao Paulo are suffering serious traffic congestion. Many cities in developing countries, which have limited road networks, high densities of population, and intense mixing of different land uses, are confronted with the rapid growth of automobile use (Kutzbach, 2008). There are a lot of policy barriers in developing countries such as the negative attitudes of the public, low transparency of government, lack of rational policy-making processes and communication, and lack of money. Therefore, explicit and more powerful traffic measures, in addition to road improvement and traffic management measures, are needed to solve this problem in developing countries (Heggie and Fon, 1991; World Bank, 2000). However, since the income effects of transport policies in less-developed countries (e.g. Taiwan) seem to be generally greater than developed countries (e.g. Sweden, Japan) (Fujii et al., 2004), political acceptability can be an insoluble problem in developing countries.

11.5.2. Strategies for overcoming barriers

Strategies for overcoming barriers are related to the various types of the barrier such as cultural, political, financial, legal, organisational, financial, and technological barriers. OPTIC (2011a) suggests a total of nine strategies to overcome barriers in the process of policy formation and implementation.

1. *Combining sticks and carrots*
2. *Trials (referendum) – a way to create legitimacy and acceptance*
3. *Communicating benefits clearly*
4. *Using good examples*
5. *Preparing for windows of opportunity*
6. *Organisational responsibility and set-up*
7. *Applying state funding to instigate municipal investments*
8. *Selection of established or innovative technical solutions*
9. *Learning from best practice*
10. *Expand the policy scope and develop flexibility in negotiations*

11.5.3. Policy packaging

Congestion charges are advocated as one of the most effective methods to facilitate the modal shift. However, charging disincentive for road users is publicly unacceptable and politically unfeasible (Ison, 2000; Jones and Salomon, 2003). In particular, the new imposition of a charge on the previously ‘free’ road may provoke reluctance to its introduction (Gullberg and Isaksson, 2009). Furthermore, citizens may recognize “negative economic policy intervention to be an encroachment of private area, or just regard it as a too extreme measure” (Sørensen et al., 2014). Sometimes, resistance to negative economic policy intervention may be resulted from a concern about the possible negative outcome in terms of equity or regressive distributive effect (Langmyhr, 1999; Whittles, 2003). In particular, since the loser is more sensitive to MSP than the winner, the loser's opposition would be massive. As a result, even effective individual measures have often proved to be politically difficult to implement. Furthermore, even strong individual policy intervention used often to produce limited effects and undesirable side effects.

Since single policy measures are not sufficient to address complex policy matters in the transport policy sector, a wide variety of policy intervention can be applied in order to increase public acceptance and enhance the probability of a successful policy. A policy package is generally defined as "a combination of individual policy measures, aimed at addressing one or more policy goals in order to improve the impacts of the individual policy measures, minimise possible negative side effects, and/or facilitate measures' implementation and acceptability" (OPTIC, 2010). Thus, the objective of the policy packaging is seeking for an effective and feasible combination of MSP to gain policy objectives such as a reduction of traffic congestion and pollution.

To overcome implementation barriers of policy intervention, the concept of primary measures and ancillary/secondary measures can be used (Givoni, 2014a). If congestion charges are introduced as a primary measure, various types of barriers may occur. In this case, any unintended effect and barrier can be dealt with by ancillary measures. Much research indicates that the combination of sticks and carrots is served as a key success factor for creating acceptance in policy formation (Sørensen et al., 2014). Sørensen et al. demonstrate in three case studies how implementing road pricing schemes and policy packaging can deal with multiple barriers. In the case of London and Stockholm's congestion charging schemes and the Swiss heavy vehicle fee scheme, strategic combination of various policy leads to a successful implementation. However, Manchester and Edinburgh congestion charging schemes are failed attempts to implement. Therefore, to get a successful formation and implementation of policy, skilfully combining and utilizing various tools are needed. The combined MSPs might be one of all the efforts to discover effective methods of overcoming policy barriers.

In this research, since the effectiveness of congestion charges is higher than the other MSPs, congestion charges can be a primary measure to reduce congestion and PT commuting cost subsidies can be an ancillary measure to mitigate the barrier. Although a subsidy for PT might be disputed from an economic perspective, it can provide social benefits, such as social inclusion (Justen et al., 2014b). However, since the combination of the two MSPs as hard measures and hard measures (sticks and carrots) results in negative synergy effect in this research (see **Chapter 6**), the consideration of combination of other types of policies, such as hard measures and soft measures, sticks and sermons, and carrots and sermons, is needed.

Meanwhile, since people may generally be concerned about the public interest as well as their interest, the normative measures (sermons) of influencing people's perception of contribution to society can be used in order to facilitate acceptability of transport policy (Jaensirisak et al., 2002). According to Donsall (2000), to persuade people to change their behaviour voluntarily, conscious-raising, the enhancement of PT service, and the increase of the price of car use can be three major instruments. In addition, Eriksson et al. (2010) indicated the importance of internal motivational factors for the reduction of car use. Increasing awareness of the positive consequences of the reduction of car use will enhance public acceptability (Gärling and Schuitema, 2007). In addition, Horrington et al. (2001) reported that a substantial environmental improvement has a positive effect on acceptability. Therefore, apart from the carrot measure, normative measures may be widely used as ancillary measures to enhance political acceptability (Schade and Schlag, 2000). Particularly, as a normative measure is more cost-effective and has no reluctance to the implementation of policy, it can be used as a basic ancillary measure.

11.6. Summary

The revenue and expenditure with the three MSPs are calculated to judge the potential of the introduction of a new MSP. The maximum annual revenue of additional parking fees from public parking lots in the Gangnam area is just 15 billion won (about £8 million) even when the level of additional parking fees is 6,000 won (£3.3) per day. The amount of annual revenue is too small to fund new transport projects. For congestion charges, if the level of the toll is 4,000 won (£2.2) per day, the annual revenue would be maximized. The annual revenue from congestion charges is calculated to be more than 431 billion won (about £240 million) under the charging of 4,000 won (£2.2) scenario. In the case of the PT commuting cost subsidy, if the level of support is 4,000 won per day, the total annual expenditure would be 613 billion won (about £340 million). Although the burden of expenses depends on the types of subsidy scheme and the distribution rate of organization concerned such as employers, local authority and central government, the degree of expenditure for PT commuting cost subsidies is too large.

Although there are many controversial debates about whether the revenue from the disincentive MSP can directly connect with the expenditure of the MSP, earmarking methods may provide the concept of the effective combination of the MSP in the financial sector. A combination of sticks and carrots can be a practical and effective method to enhance political acceptability. In addition, the consideration of combination of other types of policies, such as hard measures and soft ones, sticks and sermons, and carrots and sermons, is needed to facilitate the effectiveness of transport policy and to enhance political acceptability.

Chapter 12. Conclusion

12.1. Introduction

The main purpose of this research is to investigate what the most effective MSP is in the passenger sector, what factors significantly influence travel mode choice patterns, whether interaction effects of MSP contribute to modal shift from car to PT or not, which group is more significantly affected by a particular MSP, and which MSP is progressive or regressive in terms of equity evaluation.

This study focuses on the modal shift from car to PT because this type of modal shift is the most practical, influential, applicable and acceptable method. In addition, the three MSPs are selected as the main subject of research since the three MSPs are evaluated as the most effective MSPs through the literature review and the prior assessment. Thus, MSPs such as PT commuting cost subsidies, additional parking fees, and congestion charges are focused in the thesis.

The survey was carried out with a view to developing discrete choice models to predict the modal shift behaviour of commuters in the Gangnam area under the hypothetical MSP scenarios. The SP survey with a full factorial design was constructed to estimate the main effects and interaction effects of the three MSPs. Although twenty-seven SP choice questions made up of three levels and three MSPs are represented, the use of the on-line survey (*i*-Survey provided by University of Southampton) allows to overcome the complexity of the full factorial design. Thus, the SP data were obtained from 767 respondents, who work in the Gangnam area of Seoul, through an online survey that took place in early 2013.

Following the survey, the arrangement and analyses of SP data, the review on criteria about various models, the development of various models, the prediction of modal shift probability of travel mode, the study of segmentation method, the research of equitable assessment, and the calculation of revenues and expenditures have been conducted to achieve the objectives of the research. Although the main research is carried out by the standard logit models, the MLMs are also developed to investigate better models. During the research process, there are a lot of findings and new insights for a deeper understanding of transport policies. In particular, the result of research on the interaction effect offers numerical evidence related to modal shift synergy effects. Due to the use of a full factorial design as an experimental design, detailed research on the two-factor interaction effects can be undertaken.

This chapter summarises the main research findings. In addition, there is a consideration of the limitation of the study as well as a suggestion for future research in this area.

12.2. Main Research Findings

(1) Necessity of including interaction terms in the specification of a model

For the standard logit, the various utility functions with only alternative-specific variables are developed to investigate the most effective MSP.

All the main effect coefficients of the MSP are statistically significant at the level of 99% due to the absolute t-statistic, with over 2.57. Many coefficients of the two-factor interaction are statistically significant, even though the three-factor interaction coefficient (β_{123}) is statistically insignificant. In addition, in terms of the goodness of fit of the estimated model, the ρ^2 values of all the models with interaction terms are higher than those of models without interaction terms even though the discrepancies between them are small. This result is in line with the study of Habibian and Kermanshah (2011). Consequently, this study indicates that consideration of interaction terms is needed in this type of transport policy research because the coefficients associated with two-factor interaction terms are statistically significant and the inclusion of interaction terms in the specification of the models enhances the goodness of fit of the models. In short, models with interaction terms are more suitable for this research than models without interaction terms, although differences in fit are slight.

(2) Comparison of the modal shift effects of MSP

The utility functions with only alternative-specific variables are developed using binary logit models to assess the modal shift effects of both an individual MSP and the combined MSPs. These logit models would seem to indicate that the greatest level of modal shift would be achieved by the introduction of congestion charges, with additional parking fees the next most effective, and the lowest level of modal shift generated by the PT commuting cost subsidies. In addition, with respect to the synergistic effects of MSPs, the most powerful combination is a union between additional parking fees and congestion charges, with a combination of PT commuting cost subsidies and congestion charges the second most effective, whereas the least powerful combination is a bond between PT commuting cost subsidies and additional parking fees. This research indicates that the modal shift effect of congestion charges is higher than parking fees. This result is similar to Albert and Mahalel's research (2006).

Meanwhile, the modal shift effects of the MSP at the same monetary level of policy intervention are also compared. The order of modal shift effect is similar to the above results. However, there are some exceptions. Models A, which is a model using only the SP data based on level of MSP (e.g. support 50% of the PT commute cost), show that the modal shift effect of the PT commuting cost subsidies is higher than additional parking fees. This result seems to indicate that in the models based on psychological perspective (e.g. the percentage of government subsidy in the decision of travel mode choice), pull measures (carrots) are preferable to push measures (sticks). This result is similar to the performance of the existing research (Lee et al., 2005) on the basis of only the SP survey data.

(3) Comparison of the modal shift effect of an MSP alone and the combined two MSPs

The change point of the market share of PT can make tracking path curves according to the change of allocation ratio (e.g. subsidy 0% : parking 100% → 10% : 90% → 20% : 80%) of the two policy intervention by using models 2 (models with interaction terms, comprised of only statistically significant coefficients). The results indicate that if there is a strong interaction between them, independent implementation of one MSP alone shows a higher market share of PT than that of the combined MSPs. In this case, the simultaneous implementation of the two MSPs at the level of the equal allocation ratio of policy intervention (e.g. subsidy 50% : parking 50%) will create the lowest level of the market share of PT. This finding indicates that the equal distribution of policy intervention can make the worst results in terms of modal shift effects of MSP if there is a strong interaction between them. Meanwhile, if there is no interaction effect between the combined MSPs, one MSP, which has a higher market share of PT, would be always higher than the other MSP. This result offers clear and descriptive graphs about the influence of the interaction effect.

(4) Occurrence of the negative modal shift synergy effect

Modal shift synergy effects are measured to more accurately understand the pure interaction effects of the combined MSPs. Two methods are used to calculate modal shift synergy effect (see **Figure 6-8**). First, at the same monetary level of policy intervention, the differences between 'the average value (1/2) of the sum (e.g. 10,000 won) of modal shift probability for policy A alone (e.g. 5,000 won) and policy B alone (e.g. 5,000 won)' and 'the value of modal shift probability for a combination of policy A and policy B (e.g. 5,000 won)' can be calculated. These difference values can be regarded as "the deviated modal shift synergy effects". Although there are deviations derived from the use of average values, these deviations can be removed because the deviations have a symmetrical structure on both sides of the centre. Therefore, after deducting the deviations derived from the use of average values, the values of the rest can be regarded as "the net modal shift synergy effects". Second, another value of the modal shift synergy effect can be obtained since the discrepancy between 'the sum (e.g. 5,000 won) of the modal shift probability for policy A alone (e.g. 2,500 won) and policy B alone (e.g. 2,500 won)' and 'the value of modal shift probability for a combination of policy A and policy B (e.g. 5,000 won)' can be calculated. Although there is a little difference of the values of modal shift synergy effect between the both, the result of the calculation corresponds approximately to each other.

As with May et al.'s research (2004) indicating the occurrence of the negative synergy effect between the cordon and parking charges, this thesis indicates that the modal shift synergy effects of all the combined MSPs show negative results. The highest level of negative modal shift synergy effects would be created by the combination of additional parking fees and congestion charges, with the combination of PT commuting cost subsidies and additional parking fees the next highest, and the lowest level of negative modal shift synergy effects obtained by the combination of PT commuting cost subsidies and congestion charges. Therefore, in terms of positive modal shift synergy effects, the combination of PT commuting cost subsidies and congestion charges is the best combination. The order of the modal shift synergy effect of the combined MSPs is always the same, regardless of the type of the models (see **Table 6-11**). This research offers numerical figure of the negative modal shift synergy effect for three combinations of MSP. This result may be a good evidence of negative modal shift synergy effect. This thesis also provides the basic concept of the relationship between the synergy effect and redundancy effect (see **Figure 6-13**).

(5) Comparison of the modal shift probability curves of the combined MSPs

The market shares of PT in regards to the combined MSPs at the same monetary level of policy intervention are compared. If there are no interaction effects between the two MSPs, the market share of PT seems to be determined as the average value of each MSP. However, if there are interaction effects between the two MSPs, the market share of PT may depend on the sign and the magnitude of coefficients in the utility function.

In this research, all the coefficients of two-way interactions represent positive signs in all the models. Since all the coefficients of interaction terms belong to the utility functions of car use, it can be interpreted that the positive signs of the coefficients contribute to the increase of utility of car use. Therefore, the higher the value of the coefficients of two-way interactions, the less the modal shift effects of the combined MSPs. In addition, the higher the value of coefficients, the greater the degree of downward deviations from the average values between the individual MSPs (see **Figure 6-14 ~ 16**). In this case, these deviation values between the average values and the market share values of

PT seem to imply the negative modal shift synergy effects. This result offers clear graphs about the influence of interaction effect.

(6) Which group is more sensitive to the level of policy interventions?

Two types of segmented choice models, such as 'segmentation models using dummy variables' and 'segmentation models using separate data of segmented groups', are developed in order to deeply understand the sensitivity to level of the MSP across segmented groups, to obtain more accurate predictions about the behaviour of the segmented groups, and to identify relative and intrinsic mode preferences of the segmented groups. In this thesis, twelve segmented socio-demographic variables and seven segmented attitudinal variables are explored.

For the former models, the relative mode preferences of the segmented groups are compared since these models hold the same ASC and the same coefficients of MSP regardless of the segmented group. For example, it is discovered the fact that the market share of PT for the higher income group is lower than that of the lower income group at present (see **Appendix Figure 7-9**). This result is similar to the previous research proposing that lower income group intend to change their travel mode, but higher income group prefers to own and use a car (Dissanayake and Morikawa, 2000; Kaneko et al., 2001; Vasconcellos, 2005; Baker et al., 2005; Liu, 2006). In addition, a new finding is that all the segmented models using dummy variables are better than the default model (model B0) in terms of the goodness of fit.

In the case of the latter models, the modal shift effects of the MSP across segmented groups and the intrinsic mode preferences of each segmented group are investigated. The PT commuting cost subsidies for some segmented groups express clearly the wide variation of the modal shift effects more than other policies. For instance, it is interesting to note that the modal shift effect of the PT commuting cost subsidies for the middle-income group is very much lower than that of the other income groups (see **Appendix Figure 7-10**).

In particular, these segmentation analyses indicate that some attitudinal factors affect significantly the behaviour of travel mode choice like the research of Lee (2011a).

(7) Which income group obtains welfare benefits or losses concerning the implementation of the MSP?

The equity assessment is carried out using Rosen and Small's welfare measure formula to assess the welfare change of MSP. Two types of segmentation models (using separate data of the segmented income groups or using income dummy variables) are applied for obtaining the CVs of each MSP across the segmented income group. The two results are almost the same. First, while the PT commuting cost subsidies create welfare benefits, additional parking fees and congestion charging make welfare losses respectively. Second, as for PT commuting cost subsidies, the low-income group obtains a larger consumer benefit than the high-income group. For the additional parking fees and congestion charges, the low-income group gets smaller consumer losses than the high-income group. Additionally, as for the various segmented groups such as region, age, gender, and so on, the CVPP of each group are estimated. The result offers useful information on income variation of each group.

(8) Which MSP is progressive or regressive?

The ratio (π_h) of CVPP in the average income of each income group are analysed to judge a winner or a loser. For PT commuting cost subsidies, the absolute π_h value of the high income group is lower than the low income group. Due to their negative π_h signs, the PT commuting cost subsidy is judged to be a progressive policy. Conversely, as for the additional parking fees and congestion charges, the π_h value of the high income group is lower than the low income group. Due to their positive π_h signs, the additional parking fees and congestion charges are judged to be a regressive policy respectively. This result is in line with many existing research (May, 1992; Banister, 1994; Langmyhr, 1997; Lee et al., 2005; Schweitzer, 2009).

(9) Development of the standard logit models with commuting time and commuting cost variables

Two types of models with commuting time and cost variables are developed since travel time and cost are major variables affecting the choice of travel mode significantly. Commuting time and cost variables include 'Car Commuting Time', 'PT Commuting Cost', '(PT – Car) Commuting Time', and '(Car – PT) Commuting Cost' variable. Two types of models consist of one model in which the current toll and the current parking fee is reflected in the '(Car – PT)·Commuting Cost' variable and the other model in which these values are put into the alternative-specific variables. In terms of the orders of the modal shift effect of the MSP, the former models (i.e. models D and models E) show the same results as models comprised of alternative-specific variables (i.e. models A, models B, and models C), while the latter models (i.e. models F and models G) represent different results (see **Figure 9-2** and **Figure 9-3**). The comparison of two types of the models illustrates the distinct difference. Therefore, it can be inferred that data processing about the current toll and parking fee and the determination of the corresponding variables may significantly affect the prediction of the modal shift effect of the MSP.

(10) Development of the various mixed logit models

Various standard logit models have been developed: models with alternative-specific variables, models with generic variables, and models with additional covariates. Various MLMs, accounting for preference heterogeneity across individuals, are also developed. Overall, the absolute values of the coefficients (means) of the MLMs are greater than the standard logit models since the portion of the utility is moved from unobserved stochastic terms in the standard logit model.

In a comparison of the MLM with the alternative-specific variables and the standard logit model with the alternative-specific variables, the ρ^2 of the MLM is a little higher than that of the standard logit model. This finding corresponds to the previous research (Yannis and Antoniou, 2007). However, the ρ^2 value of the MLMs with commuting time and cost variables and the MLMs with additional covariates is sometimes higher or sometimes lower than the standard logit models. In general, the greater the number of parameters, the higher the value of the ρ^2. Although the MLM has more number of parameters than the standard logit model, the ρ^2 of the MLM is sometimes lower than that of the standard logit model. Therefore, it can be inferred that the lower ρ^2 of the MLM may stem from the increase of unimportant random effect coefficients in this research. All in all, all the MLMs seem to be not always better than the standard logit models.

In the case of the MLM with alternative-specific variables, some random effect coefficients related to the interaction effect are statistically insignificant. Furthermore, some mean coefficients associated with the interaction effect are statistically insignificant in the MLM. In addition, some MLMs with additional covariates have wrong signs (i.e. model H1: one, model H2: two, and model H3: one). If there is a wrong sign, it is inappropriate to reproduce the phenomenon in the estimated model (Cherchi and Ortúzar, 2003).

In conclusion, all the MLMs with interaction terms seem to be not always better than the standard logit models. This result corresponds to the existing study (Cherchi and Ortúzar, 2003), indicating that the MLMs do not explain taste variations better than the standard logit models with interaction terms and some confounding effect may appear.

In addition, due to the influence of the random effect, the choice probability of the travel mode usually fluctuates (see **Appendix Figure 5-2**). Therefore, accurate comparison of the prediction of the modal shift effects of the MSPs in the MLM is limited. As a result, the benefit of calibrating the MLM seems to be minor in this research.

(11) What factors strongly influence people's behaviour of travel mode choice?

Models with additional covariates such as attitudinal, socio-economic, and travel factors are developed to investigate the most influential explanatory factors affecting mode choice. To gauge the relative importance of explanatory variables in the logit model, the standardization are used, and standardized coefficients are compared. In terms of the goodness of fit of the model, the ρ^2 values of all the models with additional covariates are higher than the default model. It means that the models with additional covariates are a more appropriate model than the default model.

The covariate model with a mixture of attitudinal, socio-economic, and travel factors indicates that 'alternative-specific variables' (level of the MSP) have the most powerful influence on mode choice decisions. An interesting finding is that attitudinal factors seem to be the next most effective explanatory set of variables. The consciousness of the importance of cost, the awareness of environmental protection, and the perception of the freedom of regulation have a strong influence on the choice of travel mode. This result corresponds to existing research indicating the importance of attitudes (Bartley, 1995; Jaesnsirisak et al., 2005; Gärling and Schuitema, 2007). Consequently, this result indicates the necessity of the introduction of informative measures.

(12) How much is revenue from MSP and expenditure for MSP?

In terms of finance, the revenue and expenditure with three MSPs are calculated to judge the potential of the introduction of the new MSP. The amount of annual revenue from the additional parking fees is too small to fund new transport projects. On the other hand, since the annual revenues from the congestion charging is a large amount of money, the introduction of this charging may contribute to financial improvement. In the case of PT commuting cost subsidy, since the degree of expenditure is too large, the introduction of this policy may be called into question.

(13) Necessity of policy packaging

A combination of sticks and carrots can be a practical and effective method to enhance political acceptability. That is, since the effectiveness of congestion charging is higher than other MSPs, congestion charges can be a primary measure to reduce congestion and PT commuting cost subsidy can be an ancillary measure to mitigate the barrier. In particular, since the combination of two MSP as hard measures and hard measures (e.g. sticks and carrots) results in negative interaction effect in this research (**see Chapter 6**), the consideration of combination of other types of transport policy, such as hard measures and soft measures, sticks and sermons and carrots and sermons, is required. Another available alternative can be a normative measure. Because a normative measure can stimulate a high level of human desire and is a cost-effective method, a normative measure can be widely used as an ancillary measure to enhance political acceptability. In particular, the covariate models with attitudinal factors indicate that the attitudinal factor is the next strongest influential factor after the MSP factors (see **Table 10-13**).

(14) Comprehensive review

Table 12-l shows an assessment of the MSP in terms of effectiveness, equity, finance, and acceptability. Although this evaluation may be somewhat arbitrary, it can be helpful to get comprehensive understanding of overall policy implementation perspective.

Table 12-1. Assessment of MSP in terms of effectiveness, equity, finance, and acceptability

Criterion	MSP	Expectation	Research result	Reason (Model B2/B0)
Effectiveness for modal shift	PT subsidy	High	Relatively low effectiveness	Less effective (Middle-income group)
	Parking fee	Middle	Relatively high effectiveness	
	Congestion charge	High	Highest effective	
Equity	PT subsidy	Progressive	Progressive	Relatively larger CS
	Parking fee	Regressive	Regressive	
	Congestion charge	Regressive	Regressive	
Finance	PT subsidy	Negative	High negative	Excessive expenses
	Parking fee	Middle positive	Low positive	Small revenue
	Congestion charge	High positive	High positive	Large revenue
Acceptability (result)	PT subsidy	Positive	Possibly negative	Too large expenditure and low modal shift effect
	Parking fee	Mild negative	Mild negative	Middle modal shift effect and low revenue
	Congestion charge	High negative	Mild negative	High modal shift effect and high revenue

In general, incentive measures (carrots) may get political acceptability easily. However, the result of segmentation analysis indicates that the modal shift effects of the PT commuting cost subsidies for the middle-income group is markedly lower than the other groups (see **Appendix Figure 7-10**). In the implementation of economic incentives, the role of the middle-income class may be massive due to their political influence. The middle class may doubt the effectiveness of subsidy and excessive expenditure. Perceived effectiveness toward acceptability can be an important factor (Piriyawat et al., 2009). For these reasons, political acceptability for the PT commuting cost subsidies may be possibly low. This result may offer the reason of scarce examples of subsidy for PT users. In practice, the PT commuting cost subsidies is not very common even though many governments try to introduce this policy.

Although Eriksson et al. (2008) suggest the perceived fairness and effectiveness as important factors for acceptability, it is only rare cases that satisfy both factors in reality. In the case of congestion charging, since the effectiveness of modal shift is very high, the appropriate use of revenue may play a big role in securing political acceptability for the introduction of congestion charging in South Korea. The due procedure of introduction of the policy and proper policy packaging may also enhance political acceptability.

12.3. Limitation of the Study and Suggestion for Future Study

The main contribution of the thesis provides deeper understanding of the modal shift effect of MSPs. Despite this, there is a lot more to do in terms of further research. Some suggestions and recommendation for future study will be presented here.

First, since this research focuses on the effectiveness of the MSP from car to PT and equity assessment, the more research on efficiency perspective is needed in order to create more efficient MSP for decreasing the difference between social benefit and social cost. In this research, through the estimation of utility function from the SP survey, the modal shift probability of the MSP and the CVPP of the MSP across each income group can be obtained. In addition, expected annual revenue and expenditure of the MSP are estimated from the RP data. However, operating and private cost and external cost cannot be obtained due to the limitation of data collection. Therefore, more exact and precise social-welfare change cannot be calculated. To understand the comprehensive concept of effectiveness and efficiency of the MSP, more research on social-welfare change is needed.

Second, this research concentrates on the interaction effect of the same type of the MSP as hard measures, i.e. economic instruments. The research on the effectiveness of diverse combinations of different type of the MSP, such as hard measures and soft measures, sticks and sermons, carrots and sermons, is necessary. In particular, a normative measure may be an interesting research subject. That is, the cost-benefit analysis of the combination of an economic incentive/disincentive policy and an informative policy may provide new insight of policy packages. In addition, the result of the survey about the priority to improve PT can be facilitated (see **Table 4-12**). That is, the combination of the MSP and transport projects for faster PT services or for solving overcrowding problems can be a method to enhance political acceptability and effectiveness of the MSP.

Third, the research on interaction effect of the MSPs allows to measure the modal shift synergy effect with the numerical methods even though there is a little difference according to the analytical method. In addition, although the negative modal shift synergy effect may stem from the redundancy phenomenon, there is a limitation to understand why and to what extent the redundancy effect occurs in the transportation sector. Thus, deeper research is needed to better understand the relationship between the synergy effect and redundancy effect.

Fourth, the research on the acceptability of various MSPs is needed to introduce the MSP into the real world. Since this research focuses on the effectiveness of the MSP for modal shift, the research on political acceptability of the MSP is required to introduce and implement the MSP systematically and acceptably. In addition, in this study, to avoid the complexity of a full factorial design, binary choices were asked. However, in reality, various types of travel mode can be used. Therefore, the use of diverse choice sets may provide a more real prediction of the effectiveness of the MSP with higher accuracy. Besides the above mentioned, a lot more could be carried out to develop and advance the formation and implementation of the MSP. Therefore, much greater research is expected in the field of MSP.

REFERENCES

Agresti, A. (2002) Categorical Data Analysis, Second Edition, A John Wiley & Sons, Inc.

Ai, C. and Norton, E.C. (2003) Interaction terms in logit and probit models, Economics Lettters 80, pp. 123-129.

Albert, G. and Mahalel, D. (2006) Congestion tolls and parking fees: A comparison of the potential effect on travel behaviour, Transport Policy 13, pp. 496-502.

Albright, S. Winston, W., and Zappe, C. (2011) Data Analysis and Decision Making, Fourth Edition, South-Western, Cenage Learning.

Algers, A., Bergström, P., Dahlbeg, M. and Dillén, J.L. (1998) Mixed Logit Estimation of the Value of Travel Time, VOT 2. RTF.

Alston, J.M. and Larso, D.M. (1993) Hicksian vs. Marshallian welfare measures: why do we do what we do?, American Agricultural Economics Association.

Amador, F.J., González, R.M. and Ortúzar, J.d.D. (2005) Preference heterogeneity and willingness to pay for travel time savings, Transportation, 32(6), pp. 627-647.

Apogee Research (1997). In Meyer, D. (1999) Demand management as an element of transportation policy: using carrots and sticks to influence travel behaviour, Transportation Research Part A 33, pp. 575-599.

Aristodemou, K. (2014) New Regression Methods for Measures of Central Tendency, Ph.D. Thesis, Brunel University.

Arsham, H. (2009) Statistical Thinking for Managerial Decisions, Business Center, University of Baltimore, available at: http://home.ubalt.edu/ntsbarsh/Business-stat/opre504.htm

Baker, J., Basu, R., Cropper, M., Lall, S. and Takeuchi, A. (2005) Urban poverty and transport: the case of Mumbai, The World Bank, Policy Research Working Paper No. 3693.

Balcombe, R., Mackett, R., Paulley, N, Preston, J., Shires, J., Titheridge, H., Wardman, M. and White, P. (2004) The demand for public transport: a practical guide, TRL Report TRL 593, TRL Limited.

Banister, D. (1994) Equity and acceptability questions in internalising the social costs of transport. In Internalising the Social Costs of Transport (Paris: OECD Publications Service), pp. 153-173.

Banister, D. (2008) The sustainable mobility paradigm, Transport Policy, Vol 15, pp. 73-80.

Bartley, B. (1995) Mobility impacts, reactions and opinions, Traffic demand management options in Europe: The MIRO Project, Traffic Engineering and Control 36, pp. 596-603.

Bartlett, J.E., Kotrlik, J.W. and Higgins, C.C. (2001) Organizational Research: Determining Appropriate Sample Size in Survey Research, Information Technology, Learning, and Performance Journal, Vol. 19, No. 1, pp. 43-50.

Batley, R. and Ibáñez, J.N. (2013) Applied welfare economics with discrete choice models: implication for model specification, K-international choice modelling conference.

Ben-Akiva, M. and Lerman, S.R. (1985) Discrete Choice Analysis: Theory and Application to Travel Demand, Cambridge: The MIT Press.

Ben-Akiva, M. and Bierlaire, M. (1999) Discrete Choice Methods and Their Applications to Short Term Travel Decisions, Transportation Science Handbook Draft.

Ben-Eliyahu, A. (2014), On methods: What's the Difference between Qualitative and Quantitative Approaches? The Chronicle of Evidence-Based Mentoring.

Berg, B.L. (2007) Qualitative Research Methods for the Social Sciences, Boston, Pearson Education.

Bernard, L.L. (1939) Social Control in Its Sociological Aspects, p. 13. In: Brigham, J. and Brown, D. W. (1980) Political Implementation, pp. 9ff. Bemelmans-Videc, M.-L., Rist, R.C., and Vedung, E., Carrots, sticks, and sermons: Policy instruments and their evaluation, p. 26.

Berry, W.D. (1999) Testing for Interaction in Models with Binary Dependent Variables, Political Methodology Working Paper Archive, available at: http://www.polmeth.wustl.edu.

Bertram, D. (2006) Likert Scales are the meaning of life, CPSC 681- Topic Report, pp. 1-10, available at: poincare.matf.bg.ac.rs/~kristina/topic-dane-likert.pdf

Bhat, C.R. (1995) A Heteroscedastic Extreme Value Model of Intercity Mode Choice, Transport Research Part B, Vol. 35, No. 7, pp. 471-483.

Bhat, C.R. (1997) An Endogenous Segmentation Mode Choice Model with an Application to Intercity Travel, Transportation Science, Vol. 31, No. 1, pp. 34-48.

Bhat, C.R. (1998) Accommodating variations in responsiveness to level-of-service measures in travel model choice modelling, Transpn Res.-A, Vol. 32, NO. 7, pp. 495-507.

Bhat, C.R. (2000) Incorporating Observed and Unobserved Heterogeneity in Urban Travel Mode Choice Modelling, Transportation Science 34(2), pp. 228-238.

Bhat, C.R. (2001) Quasi-Random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model, Transport Research Part B, Vol. 35, No. 7, pp. 677-693.

Black, J. (1981) Urban Transport Planning: Theory and Practice, Baltimore: John Hopkins University Press.

Boarnet, M., Hsu, H-P. and Handy, S. (2014) Impacts of Employer-Based Trip Reduction Programs and Vanpools on Passenger Vehicle Use and Greenhouse Gas Emissions, Policy Brief, California Environmental Protection Agency, Air Resources Board.

Boxall, P.C., Adamowicz, W.L., Swait, J., Williams, M. and Louviere, J. (1996) A comparison of stated preference methods for environmental valuation, Ecological Economics 18, pp. 243-253.

Brach, A. and Wachs, M. (2005) Earmarking in the U.S. Department of Transportation Research Programs, Institute of Transportation Studies, University of California at Berkeley.

Brett, C. and Keen, M. (2000) Political uncertainty and the earmarking of environmental taxes, Journal of Public Economics, 75, pp. 315-340.

Brownstone, D. and Train, K.E. (1999) Forecasting new product penetration with flexible substitution patterns, Journal of Econometrics 89, pp. 109-129.

Brownstone, D., Bunch, D.S. and Train, K. (2000) Joint mixed logit models of stated and revealed preference for alternative-fuel vehicles, Transportation Research Part B 34, pp. 315-338.

Button, K. (1995) Road pricing as an instruments in traffic management. In Johansson, B., Mattsson, L.G. (Eds.), Road Pricing: Theory, Empirical Assessment and Policy, Kluwer Academic Publisher, pp. 35-56.

Button, K. and Verhoef, E. (1998) Road Pricing, Traffic Congestion and the Environment, Edward Elgar Publishers, UK.

Cairns, S., Sloman, L., Newson, C., Anable, J., Kirkbride, A. and Goodwin, P. (2004) Smarter choices – changing the way we travel: the influence of soft factor interventions on travel demand, Vol. 2= Case Study Reports, the Department for Transport, London.

Carpio, C., Sydorovych, O. and Marra, M. (2007) Relative Importance of Environmental Attributes Using Logistic Regression, Selected paper prepared for presentation at the Southern Agricultural Economics Association Annual Meetings.

Cherchi, E. and Ortúzar, JdD. (2003) Alternative Specific Variables in Non-Linear Utilities: Influence of Correlation, Homoscedasticity and Taste Variations, 10th International Conference on Travel Behaviour Research.

Cherchi, E., Polak, J. and Hyman, G. (2004) The impact of income, tastes and substitution effects on the assessment of user benefits using discrete choice models, European Transport Conference, Strasbourg.

Chrzan, K. and Orme, B. (2000) An overview and comparison of Design Strategies for Choice-Based Conjoint Analysis, Sawtooth Software Research Paper series.

Chung, I.H., Chung, S.Y., Lim, Y.T. and Lee, B.T. (2006) A study on Enhancing the Acceptability of Road Congestion Pricing Policy, Korea Research Institute for Human Settlement.

Cochran, W.G. (1977) Sampling techniques (3rd ed.), New York: John Wiley & Sons.

Cooksy, L.J., Mark, M.M. and Trochim, W.M.K. (2009) Evaluation policy and evaluation practice: Where do we go from here? In Trochim, W.M.K., Mark, M.M., and Cooksy, L.J. (Eds.), Evaluation policy and evaluation Practice, New Directions for Evaluation, 123, pp. 103-109.

Croissant, Y. (2012) Estimation of multinomial logit models in R: The mlogit Packages, available at: cran.r-project.org/web/packages/mlogit/vignettes/mlogit.pdf

Czepiel, S. A. (2002) Maximum Likelihood Estimation of Logistic Regression Models: Theory and Implementation, available at: http://czep.net/stat/mlelr.pdf

Daly, A.J. and Zachary, S. (1978) Improved multiple choice models. In: Hensher, D.A., Dalvi, M.Q. (Eds.), Determinants of Travel Choice. Saxon House, Sussex.

Daly, A.J., Hess, S. and Train, K.E. (2012) Assuring finite moments for willingness to pay in random coefficient models, Transportation 39(1), pp. 19-31.

Dawes, R.M. and Corrigan, B. (1974) Linear models in decision making. Psychological Bulletin, 81, pp. 95-106.

Denant-Boèmont, L. and Hammiche, S. (2009) Public Transit Capacity and Downs-Thomson Paradox: An Experiment, University of Rennes 1 and CREM – CNRS.

Department for Transport (DfT) (2011a) Behavioural insight toolkit, Social Research and Evaluation Division, The Stationery Office, London.

Department for Transport (DfT) (2011b) Creating Growth, Cutting Carbon, Making Sustainable Local Transport Happen, DfT 2011 White paper, The Stationery Office, London.

Department of Environment, Transport and the Regions (DETR) (1998a) Transport Statistics Great Britain 1998, The Stationery Office, London.

Department of Environment, Transport and the Regions (DETR) (1998b) A New Deal for Transport: Better for Everyone, the Government White Paper on the Future of Transport, The Stationery Office, London.

Dissanayake, D. and Morikawa, T. (2000) Travel demand models with the RP/SP combining technique for the developing countries, The International Conference CODATU IX, Mexico, 103-107, April 2000.

Dissanayake, D. and Morikawa, T. (2001a) Modelling vehicle usage, mode choice and trip chaining for multiple household members in developing countries, Journal of Infrastructure planning and management, Vol. IV-53, pp. 125-133.

Dissanayake, D. and Morikawa, T. (2001b) Transport policy analysis for developing countries using a nested logit model of vehicle usage, mode choice and trip-chain, Journal of Eastern Asia Society for Transport Studies, Vol.4, No.6, pp.161-173.

Dissanayake, D. and Morikawa, T. (2010) Investigating household vehicle ownership, mode choice and trip sharing decisions using a combined revealed preference/stated preference Nested Logit Model: case study in Bangkok Metropolitan Region, Journal of Transport Geography 18, pp. 402-410.

Dissanayake, D., Kurauchi, S., Morikawa, T. and Ohashi, S. (2012) Inter-regional and inter-temporal analysis of travel behaviour for Asian metropolitan cities: Case studies of Bangkok, Kuala Lumpur, Manila, and Nagoya, Transport Policy 19, pp.36-46.

Environment Protection Agency (EPA) (1998) Technical Methods for Analyzing Pricing Measures to Reduce Transportation Emissions, USEPA report, Policy (2126) Washington, DC 20460, EPA 231-R-98-006.

Eriksson, L., Garvill, J. and Nordlund, A.M. (2008) Acceptability of single and combined transport policy measures: the importance of environmental and policy specific beliefs, Transportation Research Part A 42. pp. 1117-1128.

Eriksson, L., Nordlund, A.M. and Garvill, J. (2010) Expected car use reduction in response to structural travel demand management measures, Transport Research Part F 13, pp. 327-342.

Etzioni, A. (1975) A Comparative Analysis of Complex Organization, revised and enlarged edition, The Free Press, New York.

European Commission (1995) Toward Fair and Efficient Pricing in Transport Policy Options for Internalising the External Costs of Transport in the European Union, Green Paper, COM(95) 691 final.

Felicita, C. and Banu, G.R. (2015) Strategic Management of Cloud Computing Services: Focusing on Consumer Adoption Behaviour, International Journal of Latest Trends in Engineering and Technology, Vol. 5, Issue 2, pp. 378-384.

Flinn, C. (2004) Notes on Maximum Likelihood Estimation (First part), Introduction to Econometrics, available at: http://www.nyu.edu/econ/user/flinnc/courses/0266/maximum%20likelihood% 20notes 1.pdf.

Foerster, J.F. (1981) Nonlinear and non-compensatory perceptual functions of evaluations and choice. In Stropher, P.R., Meyburg, A.H., and Brög, W. (Eds.), New Horizons in Travel Behaviour Research. D.C. Heath and Co., Lexington, Mass.

Fowkes, T. and Wardman, M. (1988) The design of stated preference travel choice experiments - with special reference to interpersonal taste variation, Journal of Transport Economics and Policy.

Fujii, S., Gärling, T. and Kitamura, R. (2001) Changes in driver's perception and use of public transport during a freeway closure: Effects of temporary structural change on cooperation in a real-life social dilemma, Environment and Behaviour 33, pp.796-808.

Fujii, S., Gärling, T., Jakobsson, C. and Jou, R.C. (2004) A cross-country study of fairness and infringement on freedom as determinants of car owners' acceptance of road pricing, Transportation 31, pp. 285-295.

Fuller, D., Hanlan, J. and Wilde, S. (2005) Market Segmentation Approaches: Do they Benefit Destination Marketers, Centre for Enterprise Development and Research, Occasional Paper No.4, pp. 1-23.

Gärling, T. and Schuitema, G. (2007) Travel Demand Management Targeting Reduced Private Car Use : Effectiveness, Public Acceptability and Political Feasibility, Journal of Social Issues, Vol. 63, 1, pp. 139-153.

Gelman, A. (2008) Scaling regression inputs by dividing by two standard deviations, Statistics in Medicine, Volume 27, Issue 15, pp. 2865-2873.

Gill, J. (2001) Interpreting interactions and interaction hierarchies in generalized linear models: issues and publications, the American Political Science Association Annual Meeting.

Givoni, M. (2014a) Addressing transport policy challenges through Policy-Packaging. Transportation Research Part A 60, pp. 1–8.

Givoni, M. (2014b) Re-assessing the Result of the London Congestion Charging Scheme, Urban Studies, available at: http://usj.sagepubl.com/

Givoni, M., Macmillen, J., Banister, D. and Feitelson, E. (2013) From Policy Measures to Policy Packages, Transport Reviews, Vol. 33, No.1, pp. 1-20.

Golias, J. and Yannis, G. (1998) Determinants of combined transport's market share, Transport Logistics, Vol.1, No.4, pp. 251-264.

Golub, A. (2010) Welfare and equity impacts of gasoline price changes under different public transportation service levels, Journal of Public Transportation, Vol. 13, No.3, pp. 1-21.

Goodwin, P.B. (1989) The 'Rule of Three': A possible solution to the political problem of competing objectives for road pricing, Traffic Engineering and Control 30 (10), pp. 495-497.

Goodwin, P.B. (1999) Transformation of transport policy in Great Britain, Transportation Research Part A 33, pp. 655-669.

Goyat, S. (2011) The Basis of Market Segmentation: a Critical Review of Literature, European Journal of Business and Management, Vol 3, No.9, pp. 45-54.

Graham-Rowe, E.J., Skippon, S., Gardner, B. and Abraham, C. (2011) Can we reduce car use and, if so, how? A review of available evidence, Transportation Research Part A 45, pp. 401-418.

Grosvenor, T. (2000) Qualitative research in the transport sector, Resource paper for the workshop on qualitative/quantitative methods, Proceedings of an International Conference on Transport Survey and Innovation, May 24-30, 1997 (Grainau, Germany), Transportation Research E-Circular, Number E-C008, August.

Gullberg, A. and Isaksson, K. (2009) Fabulous success or Insidious Fiasco. In Gullberg, A. and Isaksson, K. (Eds.), Congestion Taxes in City Traffic, Lessons Learnt from the Stockholm Trial, Nordic Academic Press, Lund, pp. 11-204.

Güller, P. (2002) The Pricing Measures Acceptance (PRIMA) research project of DG TREN, Acceptability of Transport Pricing Strategies, MC ICAM Conference, 23-24 May, Dresden.

Habibian, M. and Kermanshah, M. (2011) Exploring the role of transportation demand management policies' interactions, Scientia Iranica, Transactions A: Civil Engineering 18(5), pp.1037-1044.

Habibian, M. and Kermanshah, M. (2013) Car Commuters' Mode Change in Response to TDM Measures: Experimental Design Approach Consideration Two-way interactions, IJST, Transactions of Civil Engineering, Vol. 37. No. C+, pp. 479-490.

Han, S.Y. (2007) A Comparative Analysis on Transfer Effects to Public Transit by Regulatory and Incentive Systems –Using Market Segmentation Method with SP Data, Journal of Regulation Studies Vol. 16, No.1, pp. 221-254.

Han, S.Y. and Lee, S.W. (2006) Analysis of effectiveness on subsidizing commuting cost for public transit user, Journal of Korean Society of Transportation Vol. 24, No.1, pp. 59-72.

Hanemann, W.M. (1982) Applied welfare analysis with qualitative response models, Department of agricultural & resource economics, UCB, working paper No.241.

Hanley, N., Wright, R.E. and Adamowicz, V. (1998) Using Choice Experiments to Value the Environment, Design Issues, Current Experience and Future Prospects, Environmental and Resource Economics 11(3-4), pp. 413-428.

Harrington, W., Krupnick, A. and Alberini, A. (2001) Overcoming public aversion to congestion pricing, Transportation Research Part A, 35, pp. 93-111.

Hau, T.D. (1983) Some Hicksian and Marshallian consumer's surplus estimates in discrete choice, Economic Letters 11, pp. 203-210.

Hau, T.D. (1986) Distributional Cost-Benefit Analysis in Discrete Choice, Journal of Transport Economics and Policy, Vol 20, N0.3, pp. 313-338.

Hau, T.D. (1987) Using A Hicksian Approach to Cost-benefit Analysis in Discrete Choice: an Empirical Analysis of a Transportation Corridor Simulation Model, Transpn. Res-B, Vol. 21 B, No. 5, pp. 339-357.

Hau, T.D. (1992) Economic Fundamentals of Road Pricing, A diagrammatic analysis, working papers, Infrastructure and Urban Development, World Bank, Washington, DC.

Hausman, J.A. (1981) Exact Consumer's Surplus and Deadweight Loss, The American Economic Review, Vol. 71, pp. 662-676.

Haustein, S. and Hunecke, M. (2013) Identifying target groups for environmentally sustainable transport: assessment of different segmentation approaches, Current Opinion in Environmental Sustainability, SciVerse ScienceDirect, 5: pp. 197-204.

Haveman, R.H., Gabay, M. and Andreoni, J. (1987) Exact Consumer's Surplus and Deadweight Loss: A Correction, The American Economic Review, Volume 77, Issue 3, pp. 494-495.

Heggie, I.G. and Fon, V. (1991) Optimal user charges and cost recovery for roads in developing countries, Policy, Research, and External Affairs, Working Papers, Urban Transport Environment and Equity.

Hellström, J. and Nordström, J. (2012) Demand and welfare effects in recreational travel models: Accounting for substitution between number of trips and days to say, Transportation Research Part A, 46. pp. 446-456.

Hensher, D.A. (1976) Use and application of market segmentation, in Behavioural Travel — DemandModelling. Lexington Books, Lexington.

Hensher, D.A. (1997) Establishing a Fare Elasticity Regime for Urban Passenger Transport: Non-Concession Commuters, 21st Australasian Transport Research Forum, Adelaide, September 1997.

Hensher, D.A. and Greene, W.H. (2001) The Mixed Logit Model: The State of Practice and Warning for the Unwary, Working paper, Institute of Transport Studies Faculty of Economics and Business, The University of Sidney.

Hensher, D.A. and Button, K.J. (2003) Handbook of transport and the environment, Handbooks in transport Volume 4, Elsevier Ltd.

Hensher, D.A., Rose, J.M. and Greene, W.H. (2005) Applied Choice Analysis, A Primer, Cambridge University Press, New York.

Hess, S. and Rose, J.M. (2009) Some Lessons in Stated Choice Survey Design, Association for European Transport and Contributors.

Hine, J. and Scott, J. (2000) Seamless, accessible travel: user's views of the public transport journey and interchange, Transport Policy 7, pp. 217-226.

Hole, A.R. (2004) Forecasting the Demand for an Employee Park and Ride service using commuter's stated choices, Transport Policy, Elsevier, Vol. 11(4), pp. 355-362.

Hole, A.R. (2007) Fitting mixed logit models by using maximum simulated likelihood, The Stata Journal 7, number 3, pp. 388-401.

Hole, A.R. (2013) Mixed logit modelling in Stata: An overview, UK Stata Users Group Meeting, available at: http://www.stata.com/meeting/uk13/abstracts/materials/uk13_hole.pdf

Hone, A. and Koetse, M.T. (2014) A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands, Transportation Research Part A 61, pp.199-215.

Horner, M.W. (2004) Spatial dimensions of urban commuting: A review of major issues and the implications for future geographic research, Professional Geographer 56(2), pp.160-173.

Ibanez, G. (1992) The political economy of highway tolls and congestion pricing, Transportation Quarterly 46, pp. 343-360.

IPCC (2001) Climate Change 2001: Synthesis Report, Summary for Policymakers, Intergovernmental Panel on Climate Change, Geneva.

IPCC (2007) The Physical Science Basis, Summary for Policymakers, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Geneva.

Information Resource Management Association (IRMA) (2015) Research Methods: Concepts, Methodologies, Tools, and Applications, USA.

Ison, S. (2000) Local authority and academic attitudes to urban road pricing: a UK perspective, Transport Policy 7, pp. 269-277.

Ison, S. and Rye, T. (2006) Parking, Transport Policy 13, pp. 445-446.

Ison, S. and Rye, T. (2008) The implementation and effectiveness of transport demand management measures: An International Perspective, Ashgate Publishing Limited.

Jaensirisak, S., May, A.D. and Wardman, M.R. (2002) Acceptability of road user charging influenced by system characteristics and individuals' perspectives, Acceptability of Transport Pricing Strategies, MC ICAM Conference, 23-24 May, Dresden.

Jaensirisak, S., Wardman, M. and May, A.D. (2005) Explaining variations in public acceptability of road pricing schemes, Journal of Transport Economics and Policy 39, pp. 127-153.

Jara-Díaz, S.R. and Videla, J.I. (1989) Detection of income effect in mode choice: Theory and application, Transpn. Res. B, Vol. 23B, No. 6, pp. 393-400.

Jara-Díaz, S.R. and Videla, J.I. (1990) Welfare implication of the omission of income effect in mode choice models, Journal of Transport Economics and Policy, pp. 83-93.

Johansson, L.-O., Gustafsson, M., Falkemark, G., Gärling, T. and Johansson-Stenman, O. (2001) Goal Conflicts in Political Decision Making: A Survey of Municipality Politicians´ Views of Road Pricing.

Jong, G.D., Pieters, M., Dail, A., Graafland, I., Kroes, E. and Koopmans, C. (2005), using the logsum as an evaluation measure, Literature and case study, working paper, RAND EUROPE.

Jong, G.D., Daly, A., Pieters, M. and Hoorn, T.v.d. (2007) The logsum as an evaluation measure: Review of the literature and new results, Transportation Research Part A 41, pp. 874-889.

Jong, W.J., Han, S.Y. and Park, J.S. (2009) Tax incentive policy for public transit users, KOTI.

Jones, I.S. (1977) Urban transport appraisal, The Macmillan Press LTD, pp. 95-98.

Jones, P.M. and Bradshaw, R. (2000) The family and the school run: What would make a real difference? Summary report to the AA Foundation for Road Safety Research, University of Westminster, London.

Jones, P.M. and Sloman, L. (2003) Encouraging Behaviour Change Through Marketing and Management: What can be achieved?, 10th International Conference on Travel Behaviour Research, August 10-15.

Joshi, M.S. (1998) Journey to work: the potential for modal shift? Health Education Journal, Oxford Brookes University, Vol. 57, pp. 212-223.

Justen, A. Fearnley, N. Givoni, M. and Macmillen, J. (2014) A process for policy packaging: ideals and realities. Transportation Research A 60, pp. 9-18.

Justen, A., Schippl, J., Lenz, B. and Fleischer, T. (2014) Assessment of policies and detection of unintended effects: Guiding principles for the consideration of methods and tools in policy-packaging. Transportation Research A 60, pp. 19-30.

Kaneko, Y., Fukuda, A., Srisurapanon, V. and Oda, T. (2001) Estimation of the impact of area license scheme with multi-class user equilibrium model, Journal of the Eastern Asia Society for Transportation Studies 4, pp. 277-291.

Kara, A. and Kaynak, E. (1997) Markets of a single customer: exploiting conceptual developments in market segmentation, European Journal of Marketing, 31, 11/12, pp.873-895.

Katzev, R. (2003) Car Sharing: A New Approach to Urban Transportation Problems, analyses of social issues and public policy, Vol. 3, No. 1, pp. 65-86.

Kii, M., Hirota, K. and Minato, K. (2005) A study on modal shift potential considering public transport operation, the 9th International Conference on Computers in Urban Planning and Urban Management.

Kim, G.S. (2001) Stated Preference Design and Analysis: The First Phase, The Korea Transport Institute.

Kim, H.-G., Choi, C.-Y., Woo, J.-W., Choi, Y., Kim, K. and Wu, D.D. (2010) Efficiency of the modal shift and environmental policy on the Korean railroad, Springer-Verlag.

King, D., Manville, M. and Shoup, D. (2007) The political calculus of congestion pricing, Transport Policy, 14, pp. 111-123.

Kingham, S., Dickinson, J. and Copsey, S. (2001) Travelling to work: will people move out of their cars, Transport Policy, Vol. 8, pp. 151-160.

Kinnear, P.R. and Gray, C.D. (1999) SPSS for Windows Made Simple, Third Edition, Psychology Press Ltd.

Kocur, G., Adler, T., Hyman, W. and Aunet, B. (1982) Guide to Forecasting Travel Demand with Direct Utility Assessment – Sample experimental designs, United States Department of Transportation, Urban Mass Transportation Administration, Report UMTA-NH-11-0001-82-1, Washington DC.

Koppelman, F.S. and Bhat, C. (2006) A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models, Federal Transit Administration, US Department of Transportation, Washington, DC.

Korea Transport Database (2010) KTDB national passenger traffic survey pocket book, Seoul.

KOTI (The Korea Transport Institute) (2007) National Transport Network Study.

KOTI (The Korea Transport Institute) (2010) National passenger O/D travel survey, Korea Transport Database, National transport DB centre.

Kotler, P., Brown, L., Adam, S. and Armstrong, G. (2001) Marketing, 5th Edition, Pearson Education, Frenches Forest, Australia.

Kottenhoff, K. (1999) Evaluation of Passenger Train Concepts: Methods and Results of Measuring Travelers' Preferences in Relation to Costs, Doctoral thesis, KTH (The Royal Institute of Technology), SE-100 44, Stockholm, Sweden.

Kroes, E.P. and Sheldon, R.J. (1988) Stated Preference Methods: An Introduction, Journal of transport economics and policy, pp. 11-25.

Kutzbach, M. (2008) Motorization in Developing Countries: Causes, Consequences, and Effectiveness of Policy Options Journal of Urban Economics 65 (2), pp. 154-166.

Lamb, C. W., Fair, J. F. and McDaniel, C. (2003). Marketing. Beijing: Peking University Press.

Langmyhr, T. (1997) Managing equity, Transport Policy, 4, pp. 25-39.

Langmyhr, T. (1999) Understanding innovation the case of road pricing, Transport Reviews, Vol. 19, No. 3, pp. 255-271.

Laird, J. (2009) Transport welfare benefits in the presence of an income effect, University of Leeds, European Transport Conference 2009.

Layard, R., Mayraz, G. and Nickell, S. (2008) The marginal utility of income, Journal of Public Economics 92, pp. 1846-1857.

Leape, J. (2006) The London congestion charge, Journal of Economic Perspectives, Vol. 20, Number 4-Fall, American Economic Association, Nashville, pp. 157-176.

Lee, J.B. (2011a) Analysing the Preference Behaviour for Railway Choice and Modal Shift Policy based on Environmental Consciousness, Ph.D. Thesis, Seoul National University of Technology, South Korea.

Lee, L-F. (1992) On efficiency of methods of simulated moments and maximum simulated likelihood estimation of discrete response models, Econometrica 8, No 4, pp. 518-552.

Lee, S.W., Han, S.Y. and Park, S.S. (2005) Effective analysis on public transit user support policy - A quantitative analysis of commuting cost subsidy program, The Korea Transport Institute, South Korea.

Lee, Y.W. (2011b) The Equity and Efficiency impacts of congestion charging measures: the case of Seoul, Korea, Ph.D. Thesis, the University of Southampton.

Lindström Olsson, A-L. (2003) Factors that influence choice of travel mode in major urban areas, The attractiveness of Park & Ride, Stockholm: Department of Infrastructure, Division of Transportation and Logistics, Kungliga Tekniska Högskolan, available at: http://kth.diva-portal.org/smash/get/diva2:7499/FULLTEXT01.pdf

Litman, T. (2011), Using Road Pricing Revenue- Economic Efficiency and Equity Considerations. Victoria Transport Policy Institute, available at: http://www.vtpi.org/revenue.pdf.

Liu, G. (2006) A behavioural model of work-trip mode choice in Shanghai, Statistics Norway, Research Department, Discussion Papers, No. 444.

Lowi, J.T. (1964) American Business, Public Policy, Case-Studies, and Political Theory, World Politics, 16(4), July, pp. 677-715.

Lowi, J.T. (1972) Four System of Policy, Politics and Choice, Public Administration Review, 32(4), pp. 298-310.

Lowi, J.T. (1985) The State in Politics: The Relation Between Policy and Administration, In Noll, R.G. (Eds.) Regulatory Policy and the Social Science, Berkeley, Los Angeles, London: University of California Press, pp. 67-100.

Lumsdon, L., Downward, P. and Rhoden, S. (2010) transport for tourism: Can Public Transport Encourage a Modal Shift in the Day Visitor Market?, Journal of Sustainable Tourism, 148.

Market and Opinion Research International (MORE) (1999) Attitudes to Transport, Summary Report, Research Study Conducted for BBC Broadcast.

Marsden, G. (2006) The evidence base for parking policies – a review, Transport Policy, Vol. 13, pp. 447-457.

Marshall, S. and Banister, D. (2000) Travel reduction strategies: intentions and outcomes, Transportation Research Part A 34, Issue 5, pp. 321-338.

Matear, S.M. (1991) The Existence and Use of Benefit Segments in the Irish Sea Ferry Market, Ph. D. Thesis.

May, A.D. (1992) Road pricing: an international perspective, Transportation 19, pp. 313-333.

May, A.D., Kelly, C. and Shepherd, S. (2006) The principles of integration in urban transport strategies, Transport Policy 13(4), pp. 319-327.

McFadden, D. (1973) Conditional logit analysis of qualitative choice behaviour, Institute of Urban and Regional Development, University of California, pp. 105-142.

McFadden, D. and Reid, F. (1975) Aggregate travel demand forecasting from disaggregate behavioural models, Transportation Res. Record 534, pp. 24–37.

McFadden, D. (1976) The theory and practice of disaggregate demand forecasting for various modes of urban transportation, Urban Travel Demand Forecasting Project Working Paper 7623, Institute of Transportation Studies, University of California, Berkeley.

McFadden, D. and Train, K.E. (2000) Mixed MNL Models for Discrete Response, Journal of Applied Econometrics, Vol. 15, No. 5, pp. 447-470.

Meyer, M.D. (1999) Demand management as an element of transportation policy: using carrots and sticks to influence travel behaviour, Transportation Research Part A 33, pp. 575-599.

Ministry of Land, Transport and Maritime Affair (2011) the outlines of Land, Transport and Maritime Budget in Korea, MLTM.

Mirabel, F. and Reymond, M. (2011) Bottleneck congestion pricing and modal split: Redistribution of toll revenue, Transportation Research Part A 45, pp. 18-30.

Mogridge, M.J.H. (1997) The self-defeating nature of urban road capacity policy, Transport Policy, Vol. 4, No. 1, pp. 5-23.

Monsalve, C. (2013) Controlling Greenhouse Gas Emissions Generated by the Transport Sector in ECA: Policy Options, The International Bank for Reconstruction and Development / The World Bank.

Munizaga, M.A., Heydecker, B.G. and Ortúzar, J.d.D. (2000) Representation of heteroskedasticity in discrete choice models, Transportation Research Part B 34, pp. 219-240.

Myers, J.H. and Tauber, E. (2011) Market Structure Analysis, American Market Association, p.157.

Neal, W.D. (2005) Principles of Market Segmentation, AMA core Marketing Knowledge: Segmentation, American Marketing Association.

Neter, J., Wasserman, W. and Kutner, M.H. (1989) Applied Linear Regression Modals, 2th Edition, Irwin.

Nevo, A. (2000) A Practitioner's Guide to Estimation of Random-coefficients Logit Models of Demand, Journal of Economics & Management Strategy 9(4), pp. 513-548.

Newman, P. and Kenworthy, J. (1989) Cities and automobile dependence: an international sourcebook, Ipswich Book company.

Nurdden, A., Rahmat, R.A.O.K. and Ismail, A. (2007) Effect of Transportation Policies on Modal Shift from Private Car to Public Transport in Malaysia, Journal of Applied Science 7, ISSN 1812-5654.

O'Fallon, C., Sullivan, C. and Hensher, D. (2004). Constraints affecting mode choices by morning car commuters. Transport Policy, 11, pp. 17–29.

Onunwor, E., Miller, I. and Frank-Ito, D. (2014) Essentials of Industrial Mathematics, 2nd Edition.

OPTIC (Optimal Policies for Transport in Combination) (2010) Inventory of measures, typology of non-intentional effects and a framework for policy packaging, Deliverable 1.

OPTIC (Optimal Policies for Transport in Combination) (2011a) How to manage barriers to formation and implementation of policy packages in transport, Deliverable 5.

OPTIC (Optimal Policies for Transport in Combination) (2011b) Best practices and recommendations on policy packing, Deliverable 6.

Qrtúzar J.de D., Roncagliolo, D.A. and Velarde (1997) Interactions and independence in stated preference modelling, Proceedings of 25th European Transport Forum (PTRC), Association for European Transport, England.

Ortúzar, J.de D. and Willumsen, L.G. (2011) Modelling Transport, 4th Edition, John Wiley & Sons, Ltd.

Owens, S. (1995) From 'predict and provide' to 'predict and prevent'? : pricing and planning in transport policy, Transport Policy, Vol. 2, No. 1, pp. 43-49.

Park Y.H. and Ha H.K. (2006) Analysis of the impact of high–speed railroad service on air transport demand, Transportation Research Part E 42, pp. 95-104.

Parkhurst, G. (2000) Influence of bus-based park and ride facilities on users' car traffic, Transport Policy 7, pp. 159-172.

Parry, I.W.H. and Bento, A. (2001) Revenue Recycling and the Welfare Effects of Road Pricing, Scandinavian Journal of Economics, 103(4), pp. 645-671.

Pearce, D.W. and Nash, C.A. (1994) The social appraisal of projects: A text in cost-benefit analysis, Macmillan Education LTD.

Pearmain, D. and Kroes E.P. (1990) Stated preference techniques: a guide to practice. Steer Davies & Gleave, Hague Consulting Group, Surrey, UK.

Peng, C.Y.J., Lee, K.L. and Ingersoll, G.M. (2002) An Introduction to Logistic Regression Analysis and Reporting, the Journal of Educational Research, EBSCO, pp. 3-14.

Piriyawat, S., Van, H.T. and Fujii, S. (2009) The roles of perceived effectiveness and problem awareness in the acceptability of road pricing in Bangkok, Songklanakarin J. Sci. Technol 31 (2), pp. 181-188.

Polak, J.W. and Jones, P.M. (1997) Using stated preference techniques to examine traveller preferences and responses, Understanding Travel Behaviour in an Era of Change, Oxford, Pergamon Press, ISBN 0080423906.

Pooley, C.G. and Turnbull, J. (2000) Modal choice and modal change: the journey to work in Britain since 1890, Journal of Transport Geography 8, pp. 11-24.

Potter, S., Enoch, M., Rye, T., Black, C. and Ubbels, B. (2006) Tax treatment of employer commuting support: an international review. Transport review, 26(2), pp. 221-237.

Preston, J.M. (1991) Demand forecasting for new local rail stations and services, Journal of Transport Economics and Policy 25 (2), pp. 183-202.

Preston, J.M. (2008) Public Transport Subsidisation. In Ison, S. and Rye, T. (Eds.) The implementation and effectiveness of transport demand management measures: An International Perspective, Ashgate Publishing Limited, pp. 189-209.

Preston, J.M. (2010) What's so funny about peace, love and transport integration? Research in Transportation Economics 29, pp. 329-338.

Preston, J.M. (2012a) Integration for Seamless Transport, International Transport Forum, Discussion Paper No. 2012-01.

Preston, J.M. (2012b) Evaluation workshop on surveys & questions, Stated Preference surveys, University of Southampton.

Preston, J.M. and Almutairi, T. (2013) Transport Policy: An initial assessment of bus deregulation, Research in Transportation Economics 39, pp. 208-214.

Proost, S., Palme, d.A., Lindsey, R., Balasko, Y., Meunier, D., Quinet, E., Doll, C., Hoofd, v.d.M. and Pires, E. (2004) Revenue, Revenue Use from Transport Pricing, Theoretical Framework, REVENUE Project Deliverable 2, Funded by 5th Framework RTD Programme, ISIS, Rome, November 2004.

Revelt, D. and Train, K.E. (1998) Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level, Review of Economics and Statistics, Vol. 80, No. 4, pp. 647-657.

Revelt, D. and Train, K.E. (1999) Customer-Specific Taste Parameters and Mixed Logit, Working Paper, Department of Economics, University of California, Berkeley.

Richardson, A.D., Ampt, E.S. and Meyburg, A.H. (1995) Survey Methods for Transport Planning, EUCALYPTUS PRESS (1ST).

Rodier, C.J. and Johnston, R.A. (1998) Travel, Emissions, and Welfare Effects of Travel Demand Management Measures, Transportation research record 1598.

Rodier, C.J., Johnston, R.A. and Shabazian, D.R. (1998) Evaluation of advanced transit alternatives using consumer welfare, Transportation Research Part C 6, pp. 141-156.

Roo, G.D. and Silva, E.A. (2010) A Planner’s Encounter with Complexity, Ashgate Publishing Limited. pp. 210-211.

Rose, J.M. and Bliemer, M.C.J. (2009) Constructing Efficient Stated Choice Experimental Designs, Transport Reviews: A Transnational Transdisciplinary Journal, Vol. 29, No. 5, pp. 587-617.

Rosen H.S. and Small. K.A. (1979) Applied Welfare Economics with Discrete Choice Models, NBER working paper series, national bureau of economic research 1050 Massachusetts Avenue Cambridge MA 02138.

Rosnow, R.L. and Rosenthal, R. (1989) Definition and Interpretation of Interaction Effects, Psychological Bulletin 105(1): pp. 143-6.

Rouhani, O.M., Knittel, C.R. and Niemeier, D. (2014) Road Supply in Central London: Addition of an Ignored Social Cost, Journal of the Transportation Research Forum 53 (1), pp. 49-64.

Ruesch, M. (2001) Potentials for Modal Shift in Freight Transport. In: Conference paper STRC 2001, 1st Swiss Transport Research Conference, Monte Veritá Ascona.

Rumsey, D. (2007) Intermediate Statistics for Dummies, Wiley Publishing Inc.

Rye, T. (2002) Travel plans: do they work?, Transport Policy 9, pp. 287-298.

Sándor, Z. and Train, K. (2004) Quasi-random Simulation of discrete choice models, Transport Research Part B, 38, pp. 313-327.

Sandra, S. (2007) Elementary Statistics Using JMP, SAS Press.

Sanko, N. (2001) Guidelines for Stated Preference Experiment Design, Professional Company Project in Association with RAND Europe, A dissertation submitted for the degree of Master of Business Administration.

Santos, G. (2004) Urban Congestion Charging: A Second-Best Alternative, Journal of Transport Economics and Policy, Volume 38, part 3, pp. 345-369.

Savage, B., Kinght, B., Bacon, J., Milington, A., Bullock, H. and Buckland, J., (2011), Behavioural insight toolkit, Department for Transport, Government social research analysis of policy.

Schade, J. and Schlag, B. (2000) Acceptability of urban transport pricing, VATT Research Reports 72, Helsinki.

Scheuren, F. (2004) What is a survey, American Statistical Association.

Schlag, B. (1997) Public acceptability of transport pricing, Dresden University of Technology, available at: http://vplno1.vkw.tu-dresden.de/psycho/projekte/afford/download/IATSSRP.pdf

Schweitzer, L. (2009) The Empirical Research on the Social Equity of Gas Taxes, Emissions Fees, and Congestion Charges, Special Report 303: equity of evolving transportation finance mechanisms.

Scott, D.M. (2002) Overcoming Traffic Congestion, A Discussion of Reducing Strategies and Behavioural Responses from a North American Perspective, EJTIR 2, No 3/4, pp. 317-338.

Scottish Office (1998) Travel Choices for Scotland, The Scottish Integrated Transport White Paper, The Stationery Office, Edinburgh.

Scottish Government (2009) Review of Economic Assessment in Rural Transport Appraisal, Part 6, available at: http://www.scotland.gov.uk/publictations/2009/10/29110947/6.

Seattle government (2008), 7 Best Practices in Transportation Demand Management, Seattle Urban Mobility Plan.

Shenoy, G.V., Srivastava, U.K. and Sharma, S.C. (2002) Business Statistics, New Age International (P) Ltd Publishers.

Shoup, D. (1997) The High Cost of Free Parking, Journal of Planning Education and Research 17(1), pp. 3-20.

Sivakuma, A. (2007) Modelling Transport: A Synthesis of Transport Modelling Methodologies, Imperial College, London.

Small, K.A. and Rosen H.S., (1981) Applied Welfare Economics with Discrete Choice Models, Econometrica, Vol. 49, No 1, pp. 105-130.

Small, K.A. (1983) The incidence of congestion tolls on urban highways, Journal of Urban Economics 13, pp. 90-111.

Small, K.A. (1992) Urban Transportation Economics, Harwood fundamentals of pure and applied economics.

Sørensen, C.H., Isaksson, K., Macmillen, J. and Åkerman, J. (2014) Strategies to manage barriers in policy formation and implementation of road pricing packages, Transport Research Part A 60, pp. 40-52.

SPECTRUM (Study of Policies regarding Economic instruments Complementing Transport Regulation and the Undertaking of physical Measures) Deliverable D8 (2005) Analysis and Assessment of the Practical Impacts of Combinations of Instruments in an Urban Context.

Staus, A. (2008) Standard and Shuffled Halton Sequences in a Mixed Logit Model, University of Hohenheim.

Steg, L. and Tertoolen, G. (1999) Sustainable Transport Policy: The contribution from behavioural scientists, Public money & Management, CIPFA, pp. 63-69.

Steg, L. and Vlek, C. (1997) The role of problem awareness in willingness-to-change car use and in evaluating relevant policy measures, In Roghengatter, J.A. and Carbonell Vaya E. (Eds.) traffic and transport psychology, Pergamon Press, Oxford, UK, pp.465-475.

Steg, L. (2005) Car use: lust and must. Instrumental, symbolic and affective motives for car use, Transportation Research Part A 39, pp. 147-162.

Strompen, F., Litman, T. and Bongardt, D. (2012) Reducing Emissions through Transport Demand Management Strategies, A review of international examples, GIZ China, Transport Demand Management in Beijing, p.43.

Sullivan, C. and O'Fallon, C. (2009) Segmentation research for sustainable transport: do's and don'ts, 32nd Australasian Transport Research Forum.

Sundar Rao, P.S.S. and Richard, J. (2012) Introduction to Biostatistics and Research Methods, 5th Edition, PHI Learning.

Takama, T. and Preston, J.M. (2008) Forecasting the effects of road user charge by stochastic agent-base modelling, Transport Research Part A 42, pp. 738-749.

Takama, T., Preston, J.M. and Kim, J.-H. (2009) An analysis of road user charging and road pricing at The Upper Derwent Valley, UK, International Review of Public Administration Vol. 14, No 2.

Tavasszy, L.A. and Bliemer M.C.J. (2013) Transport Flow, Distribution and Allocation Models, Traffic Assignment and Forecasting, In Rodrigue, J.-P., Notteboom, T., and Shaw, J. (Eds.) The SAGE Handbook of Transport Studies, SAGE Publications Ltd.

Thompson, J.M. (1977) Great Cities and their Traffic, London, Gollancz.

Thorpe, N., Hills, P. and Jaensirisak, S. (2000) Public attitudes to TDM measures: a comparative study, Transport Policy 7, pp. 243-257.

Tillema, T., Ben-Elia, E., Etterma, D. and Delden, J.V. (2013) Charging versus rewarding: A comparison of road-pricing and rewarding peak avoidance in the Netherlands, Transport Policy 26, pp. 4-14.

Train, K.E. (1986) Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand, Cambridge: The MIT Press.

Train, K.E. (1998) Recreation Demand Models with Taste Variation, Land Economics, Vol. 74, No. 2, pp. 230-239.

Train, K.E. (1999) Halton Sequences for Mixed Logit, Working Paper, Department of Economics, University of California, Berkely.

Train, K.E. (2003) Discrete Choice Methods with Simulation, Cambridge University Press.

Train, K.E. and Week, M. (2004) Discrete Choice Models in Preference Space and Willingness-to-Pay Space, in Alberini, A. and Scarpa, R. (Eds), Applications of Simulation Methods in Environment and Resource Economics, R., Kluwer academic publishers.

Vasconcellos, E.A. (2005) Urban change, mobility and transport in São Paulo: three decades, three cities, Transport Policy 12, pp. 91-104.

Vedagiri, P. and Arasan V.T. (2009) Modelling Modal Shift Due to the Enhanced Level of Bus Service, Transport 24(2), pp. 121-128.

Vedung, E. (1998) Policy Instruments: Typologies and theories. In Bemelmans-Videc, M.-L., Rist, R.C., and Vedung, E. (Eds.) Carrots, sticks, and sermons: Policy instruments and their evaluation, New Brunswick, NJ: Transaction, pp. 21-58.

Vedung, E. and van der Doelen, F.C.J. (1998) The sermon: Information programs in the public policy process – Choice, effects, and evaluation. In Bemelmans-Videc, M.-L., Rist, R.C., and Vedung, E. (Eds.) Carrots, sticks, and sermons: Policy instruments and their evaluation, New Brunswick, NJ: Transaction, pp. 103-128.

Verhoef, E.T. (2000) The implementation of marginal external cost pricing in road transport: Long Run vs Short Run and First-Best vs Second-Best, Papers in Regional Science 79, pp.307-332.

Viton, P.A. (2014) Discrete-choice Logit Model with R, City and Regional Planning 5700, Civil Engineering 5700.

Vives, X. (1987) Small Income Effects: A Marshallian Theory of Consumer Surplus and Downward Sloping Demand, Review of Economic Studies, LIV, pp. 87-103.

Vlek, C. and Michon, J.A. (1992) Why we should and how we could decrease the use of motor vehicles in the future, LATSS Research: Journal of the International Association of Traffic and Safety Sciences, 15, pp. 82-93.

Wardman, M. (1988) A comparison of revealed preference and stated preference models of travel behaviour, Journal of transport economics and policy, pp. 71-91.

Wardman, M., Tight, M. and Page, M. (2007) Factors influencing the propensity to cycle to work, Transportation Research A 41(4), pp. 339-359.

Washbrook, K., Haider, W. and Jaccard, M. (2006) Estimating commuter mode choice: A discrete choice analysis of the impact of road pricing and parking charges, Transportation 33, pp. 621-639.

Whelan, G. (2003) Identifying taste variation from choice models, Association for European Transport 2003, Institute for Transport Studies, University of Leeds.

White paper (2002) European transport policy for 2010: time to decide, European Commission.

Whittles, M.J. (2003) Urban Road Pricing: Public and Political Acceptability, Ashgate, Aldershot.

Williams, H.C.W.L. (1977) On the formation of travel demand models and economic evaluation measures of user benefit, Environment and Planning, A 9(3), pp. 285-344.

Willig, R.D. (1976) Consumer's Surplus Without Apology, The American Economic Review, Vol. 66, No 4, pp. 589-597.

Winter, P.L. (2000) Transportation Demand Management, Transportation in the New Millennium, A5010: Committee on Transportation Demand Management.

Woodburn, A., Browne, M., Piotrowska, M. and Allen, J. (2007) Literature Review WM7: Scope for modal shift through fiscal, regulatory and organisational change, Transport Studies Group University of Westminster and Institute for Transport Studies University of Leeds.

Word Bank (2000) Study on Urban Transport Development, Final Report, Padeco.co.Ltd.

Yai, T., Iwakura, S. and Morichi, S. (1997) Multinomial probit with structured covariance for route choice behaviour, Transpn. Res-B, Vol. 31, No. 3, pp. 195-207.

Yannis, G. and Antoniou, C. (2007) A mixed logit model for the sensitivity analysis of Greek drivers' behaviour towards enforcement for road safety, European Transport\Transporti Europei, N. 37, pp. 62-77.

Zhou, L., Su, Q. and Winters, P.L. (2009) Telecommuting as a component of commute trip reduction program: Trend and Determinants analyses, Transportation Research Record, Journal of the Transportation Research Board, No 2135, pp. 151-159.

Zhang, X., Paulley, N., Hudson, M. and Rhys-Tyler, G. (2006) A method for the design of optimal transport strategies, Transport Policy 13, pp. 329-338.

Zuehlke, K. and Guensler, R. (2007) Employer Perceptions and Implementation of Commute Alternatives strategies, Journal of Public Transportation, Vol. 10, No. 4.

APPENDICES

Appendix 1. Questionnaire of On-line Survey

How to complete the questionnaire

No all questions are compulsory. However, to make our study a success, we need you to answer as many questions as you can. Remember, there are no right or wrong answers.

Some questions ask you to **select a box**. Please tick the box that applies to you.

Example Are you male or female? Tick one only ☑ Male ☐ Female

Other questions ask you to **type numbers or letters** in a box.

Example What is the distance from home to work? | 13 | km

Don't worry if you make a mistake – you will be able to change your response by simply selecting the appropriate new response, or re-typing your answer in a box. You will also be able to go back to any page to change a response – this can be carried out by clicking on the "PREVIOUS" button located at the bottom right-hand side of the page.

If you have any questions or concern about completing this survey, please email dsp1e11@soton.ac.uk or call 070 7151 9806 or 44 0758 894 0967

Before you begin

Are you over 18?

- ☐ **Yes** ☞ **Go to next Question**
- ☐ **No** ☞ **Thank you for your interest but you cannot take part in this survey.**

Do you have a driver licence and an available car for commuting?

- ☐ **Yes** ☞ **Go to next Question**
- ☐ **No** ☞ **Thank you for your interest but you cannot take part in this survey.**

Are you a commuter whose workplace location is in the Gangnam area?

- ☐ **Yes** ☞ **Go to next Question**
- ☐ **No** ☞ **Thank you for your interest but you cannot take part in this survey.**

How did you get to know about this survey?

- ☐ **I was invited via employer's email**
- ☐ **I received a card at a public place at lunchtime**
- ☐ **A friend/family member/acquaintance told me about it**
- ☐ **None of above**

Section A: About you and your household

1. What is the location of your home?

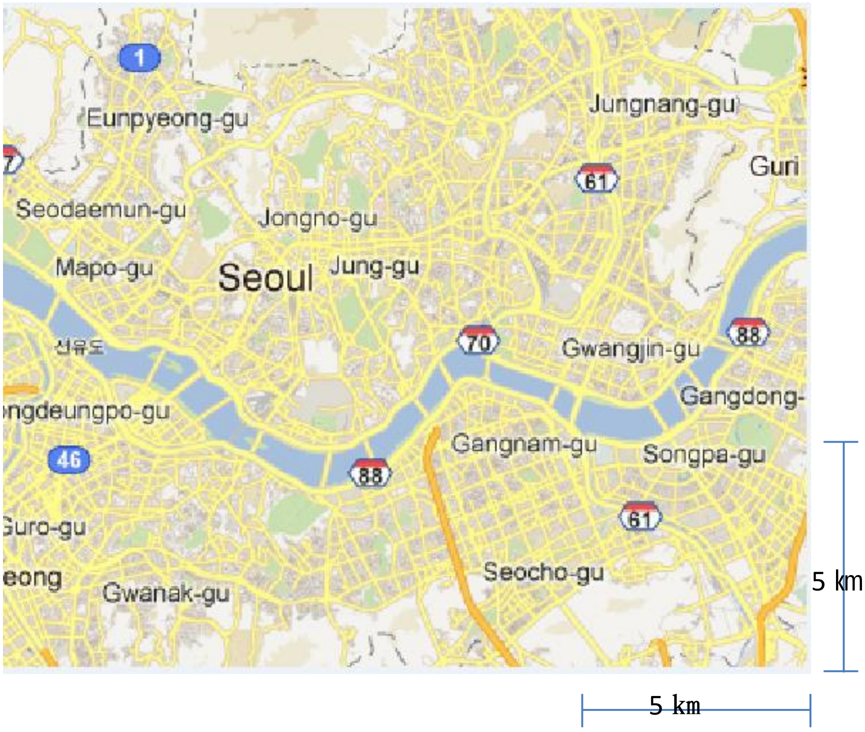
Megacity /Province <Si/Do> ( ), City/District/Region<Si/Gun/Gu> ( ),
Township<Dong/Myeon> ( )

2. What is the location of your office?

Megacity /Province <Si/Do> ( ), City/District/Region<Si/Gun/Gu> ( ),
Township<Dong/Myeon> ( )

3. What is the distance from home to work? ________Km

(Please write it based on you use most frequent routes as usual)



4. What is your main commuting transport mode?

① Car, as a driver ② Car, as a passenger ③ Car + bus
④ Car + train ⑤ Taxi + bus ⑥ Taxi + train
⑦ Bus (including transfer) ⑧ Train (including transfer) ⑨ Train + bus (including transfer)
⑩ Walk ⑪ Cycle ⑫ Taxi
⑬ Motorcycle ⑭ Other (please specify) ________.

5. When you commute from home to work, what is the frequency of the main transport mode usage over the average working days?

(When you have multi-mode travel, please check according to the criteria of main transport mode. If you never use it as commute means in a recent month, please don't check the answer ①.)

□ Car (please write on it when you have carpooling)

① Less than 1 day per week ② 1 days per week ③ 2 days per week ④ 3 days per week
⑤ 4 days per week ⑥ 5 days per week ⑦ 6 days per week ⑧ 7 days per week

□ Public transportation (bus, train) (please write on it when you use company commuting bus)

① Less than 1 day per week ② 1 days per week ③ 2 days per week ④ 3 days per week
⑤ 4 days per week ⑥ 5 days per week ⑦ 6 days per week ⑧ 7 days per week

□ Walk

① Less than 1 day per week ② 1 days per week ③ 2 days per week ④ 3 days per week
⑤ 4 days per week ⑥ 5 days per week ⑦ 6 days per week ⑧ 7 days per week

□ Cycle

① Less than 1 day per week ② 1 days per week ③ 2 days per week ④ 3 days per week
⑤ 4 days per week ⑥ 5 days per week ⑦ 6 days per week ⑧ 7 days per week

□ Other (taxi, motorcycle, etc.)

① Less than 1 day per week ② 1 days per week ③ 2 days per week ④ 3 days per week
⑤ 4 days per week ⑥ 5 days per week ⑦ 6 days per week ⑧ 7 days per week

6. What kind of vehicle type is the car you use most often?

① Compact car ② Sedan ③ Van ④ SUV ⑤ Truck ⑥ Other

7. What is the main use of your car you use most often?

① Commute to/from work ② Commute to/ from school ③ Business
④ Shopping or house usage ⑤ Leisure (sport, tour) ⑥ Other

8. How many cars do you have in your household? ① 1 ② 2 ③ 3 or more

Section B: (1) Preference Survey

A preference survey is a way of searching for the preferences of individuals and comparing various situations with the present situation if future transport circumstances are changed. This survey is comprised of various questions related to major modal shift policies to promote the use of public transportation.

To understand the basic concept easily, the definition of three policies will be presented. First, a commuting cost subsidy policy is defined as the policy of giving some money or rewards to commuters from a company to enhance the use of public transportation and deter the use of cars. Second, a parking fee policy is defined as the policy related to the increase of parking fee to deter the demand for parking in the specific area. Third, a congestion charging can be said as a way to levy the charge on entering by a car in some specific area during the certain time periods with a view to managing the transport demand in urban areas. When congestion charging is implemented, the travel time can be reduced. For example, this survey supposes a 10% reduction of total travel time under the congestion charge of 3,000 won (£ 1.65), and a 20% reduction of total travel time under the congestion charge of 6,000 won (£ 3.3).

Question about supposed situations will be presented, and you will be asked to select which mode will be selected to commute from home to work. (There are 27 supposed situations. Please state your chosen model for each of these situations.)

For example>

The supposed condition about commuting cost subsidy, parking fee and congestion charging is presented below. Under the supposed condition, you can choose your preferential selection. Please tick the box that applies to you. You can tick the box considering 27 supposed situations like this example.

Condition :	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: present level □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☑ **Use Car**

Start)

Condition : (1)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: present level □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

*** You should choose use a car when you use more than once during average ten days.**

Condition : (2)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: present level □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (3)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: present level □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (4)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: add 2,500 won more than present level per day □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (5)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: add 2,500 won more than present level per day □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (6)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: add 2,500 won more than present level per day □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (7)	when you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: add 5,000 won more than present level per day □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (8)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: add 5,000 won more than present level per day □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (9)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 0%	□ Parking fee: add 5,000 won more than present level per day □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (10)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: present level □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (11)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: present level □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (12)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: present level □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (13)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: add 2,500 won more than present level per day □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (14)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: add 2,500 won more than present level per day □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (15)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: add 2,500 won more than present level per day □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (16)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: add 5000 won more than present level per day □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (17)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: add 5000 won more than present level per day □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (18)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 50%	□ Parking fee: add 5000 won more than present level per day □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (19)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: present level □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (20)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: present level □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (21)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: present level □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (22)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: add 2500 won more than present level per day □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (23)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: add 2500 won more than present level per day □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (24)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: add 2500 won more than present level per day □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (25)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: add 5000 won more than present level per day □ Congestion charging: no charge

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (26)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: add 5000 won more than present level per day □ Congestion charging: levy 3,000 won per day *(10% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

Condition : (27)	When you use public transportation	When you use car
	□ Commuting cost subsidy: 100%	□ Parking fee: add 5000 won more than present level per day □ Congestion charging: levy 6,000 won per day *(20% reduction of total travel time)*

Choice: ☐ **Use Public Transport** ☐ **Use Car**

<Four types of questionnaire>

A type				
	classification	Subsidy	Parking fee	Congestion
1	Condition 1	0%	0 won	0 won
2	Condition 2	0%	0 won	3,000 won
3	Condition 3	0%	0 won	6,000 won
4	Condition 4	0%	2,500 won	0 won
5	Condition 5	0%	2,500 won	3,000 won
6	Condition 6	0%	2,500 won	6,000 won
7	Condition 7	0%	5,000 won	0 won
8	Condition 8	0%	5,000 won	3,000 won
9	Condition 9	0%	5,000 won	6,000 won
10	Condition 10	50%	0 won	0 won
11	Condition 11	50%	0 won	3,000 won
12	Condition 12	50%	0 won	6,000 won
13	Condition 13	50%	2,500 won	0 won
14	Condition 14	50%	2,500 won	3,000 won
15	Condition 15	50%	2,500 won	6,000 won
16	Condition 16	50%	5,000 won	0 won
17	Condition 17	50%	5,000 won	3,000 won
18	Condition 18	50%	5,000 won	6,000 won
19	Condition 19	100%	0 won	0 won
20	Condition 20	100%	0 won	3,000 won
21	Condition 21	100%	0 won	6,000 won
22	Condition 22	100%	2,500 won	0 won
23	Condition 23	100%	2,500 won	3,000 won
24	Condition 24	100%	2,500 won	6,000 won
25	Condition 25	100%	5,000 won	0 won
26	Condition 26	100%	5,000 won	3,000 won
27	Condition 27	100%	5,000 won	6,000 won

B type
Changed order
Condition 1
Condition 2
Condition 3
Condition 10
Condition 11
Condition 12
Condition 19
Condition 20
Condition 21
Condition 4
Condition 5
Condition 6
Condition 13
Condition 14
Condition 15
Condition 22
Condition 23
Condition 24
Condition 7
Condition 8
Condition 9
Condition 16
Condition 17
Condition 18
Condition 25
Condition 26
Condition 27

C type
Changed order
Condition 1
Condition 10
Condition 19
Condition 4
Condition 13
Condition 22
Condition 7
Condition 16
Condition 25
Condition 2
Condition 11
Condition 20
Condition 5
Condition 14
Condition 23
Condition 8
Condition 17
Condition 26
Condition 3
Condition 12
Condition 21
Condition 6
Condition 15
Condition 24
Condition 9
Condition 18
Condition 27

D type
Changed order
Condition 1
Condition 10
Condition 19
Condition 2
Condition 11
Condition 20
Condition 3
Condition 12
Condition 21
Condition 4
Condition 13
Condition 22
Condition 5
Condition 14
Condition 23
Condition 6
Condition 15
Condition 24
Condition 7
Condition 16
Condition 25
Condition 8
Condition 17
Condition 26
Condition 9
Condition 18
Condition 27

(2) About individual perception and attitude

To what extent do you agree with the following statements? (tick one only)

1. **Congestion problems are very severe during the morning peak.**

   ① Strongly agree ② Agree ③ Neutral ④ Disagree ⑤ Strongly disagree

2. **The use of public transport is important to reduce global warming and to protect the environment.**

   ① Strongly agree ② Agree ③ Neutral ④ Disagree ⑤ Strongly disagree

3. **The use of public transport is helpful for my health.**

   ① Strongly agree ② Agree ③ Neutral ④ Disagree ⑤ Strongly disagree

4. **The freedom of choosing transport modes should not be restricted by government regulation.**

   ① Strongly agree ② Agree ③ Neutral ④ Disagree ⑤ Strongly disagree

5. **Convenience is a very important factor in determining commuting.**

   ① Strongly agree ② Agree ③ Neutral ④ Disagree ⑤ Strongly disagree

6. **Time is a very important factor in determining commuting.**

   ① Strongly agree ② Agree ③ Neutral ④ Disagree ⑤ Strongly disagree

7. **Cost is a very important factor in determining commuting.**

   ① Strongly agree ② Agree ③ Neutral ④ Disagree ⑤ Strongly disagree

Section C: (1) About your usage of a private car for commuting

Think about using a car in commuting from home to work.

(If you don't use cars, you can omit the questions below. Please go to next page.)

1. What is the total travel time on average? (e.g. 01 hrs 10 mins) ____ Hrs ____ mins

2. What is the departure time from home?(e.g. 07: 40 am) ____

3. What is the arrival time of a workplace?(e.g. 08: 40 am) ____

* You should write about journey time based on arrival time to the entrance of parking lot.

4. What is the parking time? (e.g. 08: 45 am) ____

* You should write about parking time based on the time getting off the vehicle.

5. What is the arrival time of your office? (e.g. 08: 50 am) ____

6. How much is your total commute cost from home to work? (one direction) 14,500 won

* When you share a car or use carpooling, please write total commute cost.

6-1. How much is fuel cost? **(one direction)** (e.g. 5,000 won) ____ won

6-2. How much is toll charge? **(one direction)** (e.g. 1,000 won) ____ won

6-3. How much is parking fee? **(one direction)** (e.g. 8,000 won) ____ won

6-4. How much is other cost? **(one direction)** (e.g. boat fee 500 won) ____ won

7. Do you usually share a car with other people while commuting? * If no, go to next question

① Yes ② No

7-1. If you usually share a car, how many people do you share with the car?

① 1 ② 2 ③ 3 ④ 4 or more

7-2. How many people except for family members do you share with the car?

① 0 ② 1 ③ 2 ④ 3 ⑤ 4 or more

(2) About your usage of public transport for commuting

Think about using public transport in commuting from home to work.
(If you don't use public transport or company shuttle bus, you can omit this question. Please go to next page.)

1. What is the total travel time on average? (e.g. 01 Hrs 10 mins) ☐ hrs ☐ mins

2. What is the departure time from home? (e.g. 07: 40 am) ☐

3. What is your travel mode from home to station or bus stop?

① Walking ② Town bus ③ Car ④ Taxi ⑤ Cycle ⑥ Motorcycle
⑦ Other (please specify) ____________.

3-1. What time is your waiting for a town bus on average? ☐ minutes

4. Does your company provide a company commuting bus? * If no, go to question 1-2.

① Yes ② No

4-1. Do you usually use a company shuttle bus?

① Yes (If 'yes', go to question 3) ② No (If 'no', go to question 2)

4-2. If you don't use a company commuting bus, what is the reason?

① Mismatching time ② Access limitation ③ Dirty or noise atmosphere
④ Not enough seat or crowded bus ⑤ Other (please specify) ____________.

4-3. What is the frequency you use a company commuting bus? ☐ day per week

4-4. How much is your burden per day when you use a company commuting bus?

① Free ② Other (please specify) ☐ won for one usage

5. What time is your waiting for a bus or train on average? ☐ minutes

6. What time do you get on the vehicle? (e.g. 08: 05 am) ☐

7. Do you transfer during the journey? ① Yes ② No **(If no, go to next question)**

7-1. What is the frequency you transfer? ☐ number of times

* Please except for when moving on town bus to stations or bus stops

7-2. How long does it take to transfer?

⦿ First transfer ☐ minutes
⦿ Second transfer ☐ minutes
⦿ Third transfer or more ☐ minutes

8. At what time do you get off the vehicle? (e.g. 08: 35 am) [ ]

9. What is your travel mode from the station or bus stop to work?

① Walking ② Town bus ③ Car ④ Taxi ⑤ Cycle
⑥ Motorcycle ⑦ Other (please specify) ____________.

9-1. What time is your waiting for a town bus on average? [ ] minutes

10. What time do you arrive at work? (e.g. 08: 40 am) [ ]

11. How much is your total commuting cost from home to work? (one direction) 5,150 won

*** If you always use a free company commuting bus, go to next question**

11-1. How much is public transport fare? **(one direction)** (e.g. 1,150 won) [ ] won

11-2. How much is taxi fare? **(one direction)** (e.g. 3,000 won) [ ] won

11-3. How much is other cost? **(one direction)** (e.g. cycle fare 1,000 won) [ ] won

(3) About your commuting journey

1. What is the reason for using a car in the commuting journey?

(You can tick up to two)

① To save travel cost

② To save travel time

③ Because of the limitation of access to public transport (E.g.: too far from home)

④ Because of the difficulty of transfer in using public transport

⑤ Because of the convenient, comfortable and clean atmosphere in car
(E.g.: disliking crowded bus or subway)

⑥ Because of no need of taking a walk

⑦ Because of no need of waiting for a bus or a train

⑧ Because of the need of using car to do business or individual purpose during the work hour

⑨ Because of the frequent of extra work after working hours

⑩ To carry other people (e.g. carpooling, to commute to school for children, etc.)

⑪ Other (please specify) ___________.

2. What is the reason for using public transport in the commuting journey?

(You can tick up to two)

① Because of the limitation of parking space or parking access in the workplace

② Because of the expensive parking fee

③ To save money related to car operating cost such as fuel and toll, etc.

④ To save travel time

⑤ To enjoy extra time while commuting (e.g. sleeping, reading book, playing mobile game, etc.)

⑥ To secure the punctuality to work

⑦ To contribute to environmental protection

⑧ To reduce stress from while driving (e.g. disliking driving, congestion problems, etc.)

⑨ To secure the safety

⑩ Because of the frequent extra activities after work hour (e.g. alcohol consumption etc.)

⑪ Other (please specify)___________.

3. What is the priority to improve the public transportation?

(You can tick up to two)

① Faster services (e.g. provision of faster trains or buses, expansion of exclusive bus lane, etc.)

② More frequent services (e.g. reduction of headway intervals)

③ Better connection with the same or other public transport
(e.g. transfer improvement, change of bus route, etc.)

④ Reducing overcrowding and the provision of sufficient seats

⑤ Improving station or bus stop access
(e.g. construction of moving walk and escalator, more shuttle bus, etc.)

⑥ Cheaper fares (e.g. sales of discount tickets or decrease of public transport fare)

⑦ Reliable services (e.g. on time services etc.)

⑧ Nicer vehicles and facilities
(e.g. improving air condition or noise, clean restroom, proper temperature, etc.)

⑨ More available information
(e.g. providing more route information, arrival/departure information etc.)

⑩ Improving security (e.g. more CCTV cameras)

⑪ Other (please specify)___________.

Section D: (1) About your parking

(If you don't use a car, you can omit these questions.)

1. What kind of parking lot do you use in commuting on an average daily basis? (tick one only)

① Parking lot in workplace ② On-street parking lot ③ Off-street private parking lot
④ Off-street public parking lot ⑤ Private parking lot in the building
⑥ Public parking lot in the building ⑦ Other (please specify) ____________.

2. What is the way of paying for parking fee?

① Free parking ② By parking hour ③ By daily
④ By weekly ⑤ By monthly ⑥ Other (please specify) ____________.

3. Do you receive any subsidy or support related to parking fee from your company?

① Free parking ② All the parking fees supported from company
③ Sharing cost between you and your company ④ Your burden

4. How much is your average parking fee related to commuting a month? [ ] won

5. How much is parking fee support from your company a month? [ ] won

(2) About commuting subsidization

1. Does your company give you a commute grant? *** If no, go to question 3**

(not including the commute reward included in salary and the provision of company commute bus)

① Yes ② No *** If no, go to question 2**

2. What is the way of receiving commuting grants from your company by month?

① All the cost paid from company
② Partial cost paid from company by a fixed rate payment
③ Partial cost paid from company by a fixed sum payment
④ Other (please specify) ____________.

2-1. What is the ratio if you get partial cost by fixed-rate payment from your company? [ ] %

2-2. How much is it if you get a fixed sum payment from your company per month? [ ] won

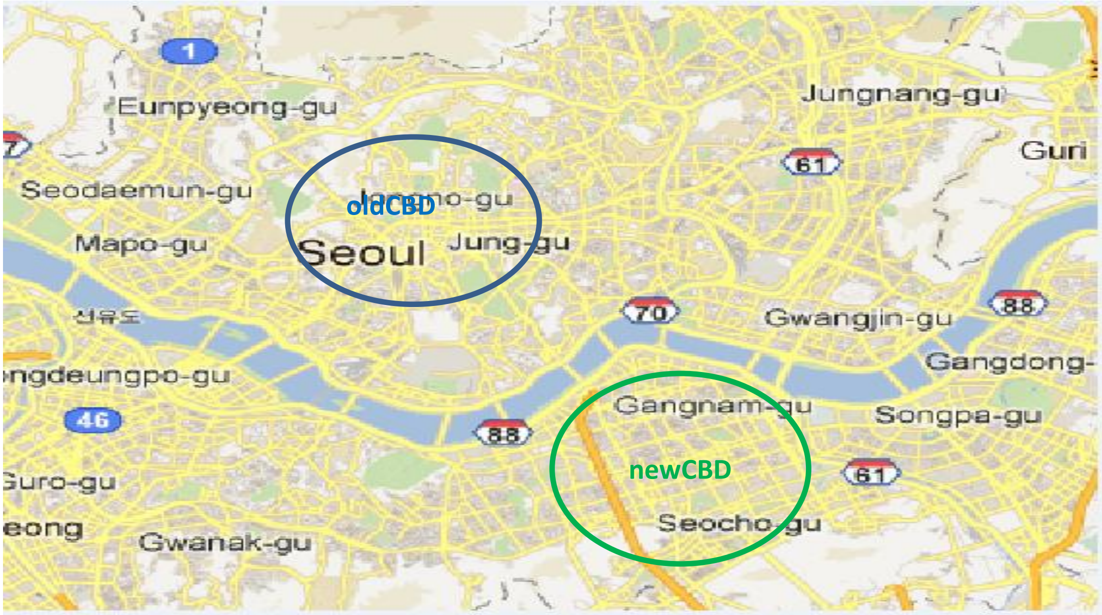
3. How much is your average total commute cost a month? [ ] won

* It can be assumed that 21 days are the average working days of ordinary workers per month considering the date of several holidays in Korea

(3) About congestion charging

1. If congestion charge should be introduced, where is the most appropriate cordon in Seoul city?

① Gangnam area (Gangnam-Gu, Seocho-Gu : new CBD)
② four big gate area (Jongro-Gu, Jung-Gu: old CBD)
③ Gangnam area and four big gate area
④ Other (please specify) ____________.



2. If congestion charge should be introduced, what is the appropriate level of charge per day?

① 2,000 won (about £1.10) ② 3,000 won (about £ 1.65) ③ 4,000 won (about £2.20)
④ 5,000 won (about £2.76) ⑤ 6,000 won (about £ 3.3) ⑥ 7,000 won (about £3.85)
⑦ 8,000 won (about £4.41) ⑧ 9,000 won (about £ 4.96) ⑨ Other (please specify) ________.

3. If congestion charge should be introduced, what is the appropriate application time?
(Suppose from Monday to Friday)

① 07:00-18:00 ② 07:00-21:00 ③ 07:00-15:00 ④ 07:00-10:00
⑤ 10:00-17:00 ⑥ 17:00-21:00 ⑦ 12:00-21:00 ⑧ Other (please specify) _______.

4. How much would you be willing to pay to reduce your commute time by 10 minutes?

① 1,000 won (about £0.55) ② 1,300 won (about £0.72) ③ 1,600 won (about £0.88)
④ 1,900 won (about £1.05) ⑤ 2,200 won (about £1.21) ⑥ 2,500 won (about £1.38)
⑦ 2,800 won (about £1.54) ⑧ 3,100 won (about £1.71) ⑨ Other (please specify) ________.

5. How much traffic delay time do you experience when you commute from home to work?

① Delay of 5 minutes or less ② Delay of 5-10 minutes ③ Delay of 10-15 minutes
④ Delay of 15-20 minutes ⑤ Delay of 20 minutes or more ⑥ I did not experience a delay

(4) About Modal Shift Policy (MSP)

1. What is the most effective and acceptable MSP in the short run (1-2 years)?
(You can tick up to two)

① Strengthening parking control (e.g. strengthening the 10th-day-no-driving system etc.)
② Increasing parking fee
③ Levying congestion charge on a certain cordon
④ Providing commute cost subsidy from the company
⑤ Increasing fuel price
⑥ Holding travel awareness campaigns
⑦ Stimulating car sharing or car pooling
⑧ Providing more available travel information
⑨ Improving the quality of public transport service
⑩ Other (please specify) ____________.

2. What is the most effective and acceptable MSP in the long run (more than five years)?
(You can tick up to two)

① Reducing parking space close to workplace
② Increasing car operating cost
③ Constructing new subway or BRT
④ Constructing 'park and ride' outside the urban area
⑤ Improving public transport facilities
⑥ Bicycle revitalization
⑦ Transit-Oriented Development (e.g. car free development)
⑧ Substitution of communications for travel (e.g. teleworking, E-shopping)
⑨ Spread alternative working patterns (e.g. flex time)
⑩ Other (please specify) ____________.

3. If it is impossible for you to use your car for commuting from home to work, which type of commute mode will be your use?

① Bus ② Train or subway ③ Bus + train or subway ④ Other (please specify) ____________.

Section E: About you and your household

1. Are you male or female? (tick one only) ① Male ① Female

2. How old are you? ① Less than 20s ② 30s ③ 40s ④ 50s ⑤ more than 60s

3. What is your total household income from all sources before tax per month? (£1= 800 won)

① Up to 1,000,000 won (£556)
② 1,000,001 won – 2,000,000 won (about £557 - £1,111)
③ 2,000,001 won – 3,000,000 won (about £1,112 - £1,667)
④ 3,000,001 won – 4,000,000 won (about £1,668 - £2,222)
⑤ 4,000,001 won – 5,000,000 won (about £2,223 - £2,778)
⑥ 5,000,001 won – 6,000,000 won (about £2,779 - £3,333)
⑦ 6,000,001 won – 7,000,000 won (about £3,334 - £3,889)
⑧ 7,000,001 won - 10,000,000 won (about £3,890 - £5,556)
⑨ More than 10,000,001 won (over about £5,557)

4. What is your highest educational career?

① No education ② Primary school ③ Middle school
④ High school ⑤ College ⑥ University
⑦ Postgraduate school

5. What is your occupational sector?

① Governmental sector ② Specialized sector ③ Administrative or clerical sector
④ Technical sector ⑤ Sales sector ⑥ Service sector
⑦ Production, drive or labour sector ⑧ Other

6. Do you have difficulties of using public transport, for example, due to physical disabilities?

① Yes ② No

7. What is your household size? ① 1 ② 2 ③ 3 ④ 4 ⑤ 5 ⑥ 6 ⑦ 7 or more

8. Do you have a child or children who commute to schools, nurseries or infant caring facilities?

① Yes ② No

9. How many workers are in your household? ① 1 ② 2 ③ 3 or more

CONGRATULATIONS YOU'VE COMPLETED THE QUESTIONNAIRE, THANK YOU!

Researchers from the Centre for Sustainable Travel Choices wish to invite you to take part in a follow-up survey next year. Please select "Yes" if you agree to be contacted next year for the follow-up survey or "No" if you would prefer not to be contacted.

Please note that by selecting "Yes" you do not agree to take part in additional studies, simply that you agree to be contacted. Also, if you wish to be contacted for the follow-up survey, your email address should be provided on the next page as the research team does not have any of your contact details.

Yes ❑ I agree to be contacted by a researcher regarding the follow-up survey next year.

** Please provide your email address on the next page.*

No ❑ I do not wish to be contacted by a researcher regarding the follow-up survey next year.

Once you provide your email address, you will be entered into a prize draw to win one of twenty £25 gift vouchers.

Email	

Appendix 2. Calculation of the Utility Value of Travel Mode and the Choice Probability of Travel Mode

[Case 1]

The estimated choice probability of car usage and PT usage calculated by using **Equation 5-22** and **Equation 5-23** in Chapter 5 is the same as that of **Appendix Table 2-1** (see blue coloured cell).

Appendix Table 2-1. The observed choice probability and the estimated choice probability of travel mode in model A2

	Subsidy level	Parking Level	Congestion level	Observed probability of car use	Utility Value of car use	Utility Value of transit use	Exponential utility value of car use	Exponential utility value of PT use	Market share rate of travel mode (%)	
									Car	PT
c1	0	0	0	0.7015	0.7331	0	2.081523	1	67.55	32.45
c2	0	0	1	0.4396	-0.2514	0	0.777711	1	43.75	56.25
c3	0	0	2	0.2166	-1.2359	0	0.290573	1	22.52	77.48
c4	0	1	0	0.4786	-0.0595	0	0.942236	1	48.51	51.49
c5	0	1	1	0.2636	-0.8592	0	0.423501	1	29.75	70.25
c6	0	1	2	0.1590	-1.6589	0	0.190348	1	15.99	84.01
c7	0	2	0	0.2988	-0.8521	0	0.426518	1	29.90	70.1
c8	0	2	1	0.1875	-1.467	0	0.230616	1	18.74	81.26
c9	0	2	2	0.1277	-2.0819	0	0.124693	1	11.09	88.91
c10	1	0	0	0.4768	0.7331	0.7173	2.081523	2.048894	50.39	49.61
c11	1	0	1	0.3258	-0.102	0.7173	0.90303	2.048894	30.59	69.41
c12	1	0	2	0.1694	-0.9371	0.7173	0.391762	2.048894	16.05	83.95
c13	1	1	0	0.3609	0.0675	0.7173	1.06983	2.048894	34.30	65.7
c14	1	1	1	0.1960	-0.5828	0.7173	0.558333	2.048894	21.41	78.59
c15	1	1	2	0.1262	-1.2331	0.7173	0.291388	2.048894	12.45	87.55
c16	**1**	**2**	**0**	**0.2174**	**-0.5981**	**0.7173**	**0.549855**	**2.048894**	**21.16**	**78.84**
c17	1	2	1	0.1372	-1.0636	0.7173	0.345211	2.048894	14.42	85.58
c18	1	2	2	0.1052	-1.5291	0.7173	0.216731	2.048894	9.57	90.43
c19	2	0	0	0.3134	0.7331	1.4346	2.081523	4.197965	33.15	66.85
c20	2	0	1	0.2136	0.0474	1.4346	1.048541	4.197965	19.99	80.01
c21	2	0	2	0.1117	-0.6383	1.4346	0.52819	4.197965	11.18	88.82
c22	2	1	0	0.2483	0.1945	1.4346	1.214703	4.197965	22.44	77.56
c23	2	1	1	0.1352	-0.3064	1.4346	0.736092	4.197965	14.92	85.08
c24	2	1	2	0.0921	-0.8073	1.4346	0.446061	4.197965	9.61	90.39
c25	2	2	0	0.1489	-0.3441	1.4346	0.708858	4.197965	14.45	85.55
c26	2	2	1	0.0949	-0.6602	1.4346	0.516748	4.197965	10.96	89.04
c27	2	2	2	0.0851	-0.9763	1.4346	0.376702	4.197965	8.23	91.77

Appendix Figure 2-1 shows the alternative calculation of the estimated choice probability of car and PT usage by using an integrated utility function. As a result, the estimated choice probability of car usage (21.16%) and PT usage (78.84%) are the same as the values in **Equation 5-22** and **Equation 5-23**.

Appendix Figure 2-1. The alternative calculation of the choice probability of both car usage and PT usage by using an integrated utility function

$$\mathrm{U}_{car} - \mathrm{U}_{PT} = \beta_0 - \beta_1 \cdot Subsidy_j + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy \cdot Congestion_j + \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j + \varepsilon_{car} - \varepsilon_{PT}$$

$$\mathrm{V}_{car} - \mathrm{V}_{PT} = 0.7331 - (0.7173) \cdot Subsidy_j + (-0.7926) \cdot Park_j + (-0.9845) \cdot Congestion_j + (0.127) \cdot Subsidy_j \cdot Park_j + (0.1494) \cdot Subsidy_j \cdot Congestion_j + (0.1848) \cdot Park_j \cdot Congestion_j$$

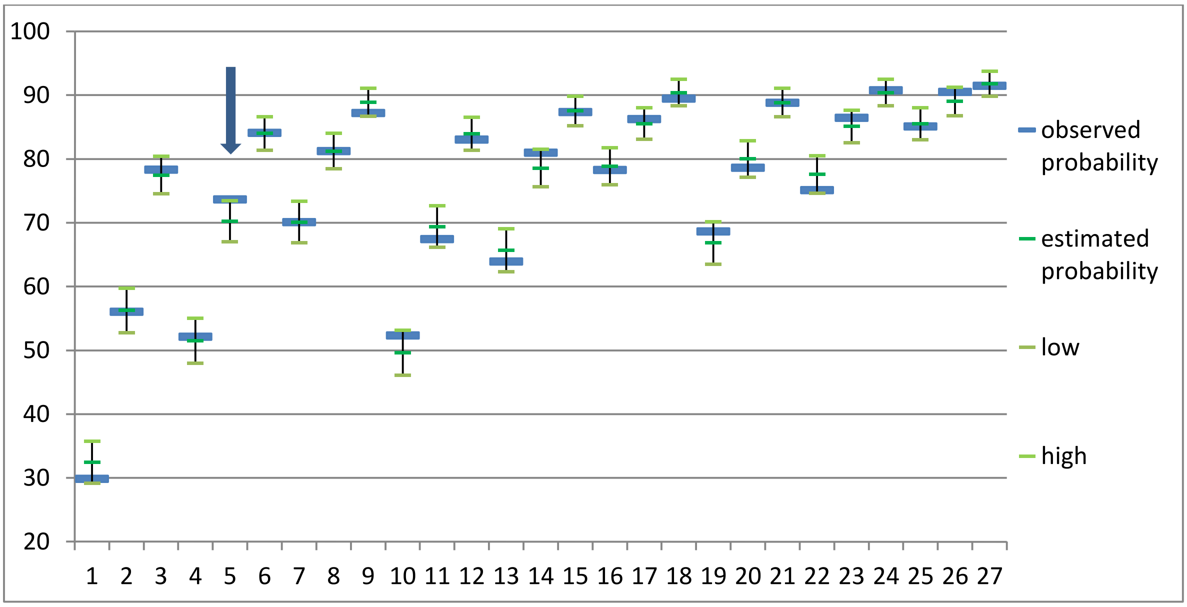
$$\mathrm{V}_{car} = 0.7331 - (0.7173) \cdot (1) + (-0.7926) \cdot (2) + (-0.9845) \cdot (0) + (0.127) \cdot (1) \cdot (2) + (0.1494) \cdot (1) \cdot (0) + (0.1848) \cdot (2) \cdot (0) = -1.3154, \qquad \mathrm{U}_{car} = e^{-1.3154} = 0.268367$$

$$P^i_{car} = \frac{1}{1 + (1/e^{V_{i,car}})} = \frac{1}{1 + (\frac{1}{e^{(-1.3154)}})} = 0.211585 \cong \mathbf{21.16\%}$$

$$P^i_{PT} = 1 - P^i_{car} = 1 - 0.211585 = 0.788415 \cong \mathbf{78.84\%}$$

Appendix Table 2-2 shows the observed probability of PT usage, the estimated probability of PT usage, 95% confidence low interval of probability, 95% confidence high interval of probability, and the difference between the observed probability and estimated probability. For instance, if congestion charges levying 3,000 won on car users are implemented (under the C3), the expected probability of PT usage (77.48%) is placed at a minimum of 74.53%, a maximum of 80.44% at the 95% confidence interval.

Appendix Figure 2-1. 95% confidence interval of probability of PT (model A2)



As can be seen in **Appendix Figure 2-1**, the 95% confidence intervals of estimated probability of PT usage are shown. In most cases, the observed probability of PT usage is placed within the 95% confidence interval. Since most of the observed probabilities of PT usage do not deviate from the confidence interval, model A2 are suitable for estimating the probability of PT. However, in the case of C5 on X-axis, the observed probability of PT usage deviates from the 95% confidence interval of estimated probability of PT usage(see C5 in **Appendix Table 2-2**). It can be inferred that the estimated probability of PT usage under the condition 5 is overestimated (see blue arrow).

Appendix Table 2-2. The estimated probability and observed probability of travel mode (level)

Condition	Subsidy level	Parking Level	Congestion Level	Subsidy & parking	Subsidy & Congestion	Parking & Congestion	Three policies	**Observed probability of PT**	**Estimated Probability of PT**	95% confidence low interval of probability	95% confidence high interval of probability	Difference
c1	0	0	0	0	0	0	0	**0.2985**	0.3245	0.2914	0.3576	-0.0260
c2	0	0	1	0	0	0	0	**0.5604**	0.5625	0.5274	0.5976	-0.0021
c3	0	0	2	0	0	0	0	**0.7834**	0.7748	0.7453	0.8044	0.0086
c4	0	1	0	0	0	0	0	**0.5214**	0.5149	0.4795	0.5502	0.0065
c5	0	1	1	0	0	1	0	**0.7364**	0.7025	**0.6701**	**0.7348**	**0.0339**
c6	0	1	2	0	0	1	0	**0.8410**	0.8401	0.8142	0.8660	0.0009
c7	0	2	0	0	0	0	0	**0.7012**	0.7010	0.6686	0.7334	0.0002
c8	0	2	1	0	0	1	0	**0.8125**	0.8126	0.7850	0.8402	-0.0001
c9	0	2	2	0	0	2	0	**0.8723**	0.8891	0.8669	0.9114	-0.0168
c10	1	0	0	0	0	0	0	**0.5232**	0.4961	0.4607	0.5314	0.0271
c11	1	0	1	0	1	0	0	**0.6742**	0.6941	0.6615	0.7267	-0.0199
c12	1	0	2	0	1	0	0	**0.8306**	0.8395	0.8135	0.8655	-0.0089
c13	1	1	0	1	0	0	0	**0.6391**	0.6570	0.6234	0.6906	-0.0179
c14	1	1	1	1	1	1	1	**0.8100**	0.7859	0.7568	0.8149	0.0241
c15	1	1	2	1	1	1	1	**0.8738**	0.8755	0.8521	0.8989	-0.0017
c16	1	2	0	1	0	0	0	**0.7826**	0.7884	0.7595	0.8173	-0.0058
c17	1	2	1	1	1	1	1	**0.8628**	0.8558	0.8309	0.8807	0.0070
c18	1	2	2	1	1	2	1	**0.8948**	0.9043	0.8835	0.9252	-0.0095
c19	2	0	0	0	0	0	0	**0.6866**	0.6685	0.6352	0.7018	0.0181
c20	2	0	1	0	1	0	0	**0.7864**	0.8001	0.7718	0.8284	-0.0137
c21	2	0	2	0	2	0	0	**0.8883**	0.8882	0.8659	0.9105	0.0001
c22	2	1	0	1	0	0	0	**0.7514**	0.7756	0.7461	0.8051	-0.0242
c23	2	1	1	1	1	1	1	**0.8648**	0.8508	0.8256	0.8760	0.0140
c24	2	1	2	1	2	1	1	**0.9079**	0.9039	0.8831	0.9248	0.0039
c25	2	2	0	2	0	0	0	**0.8510**	0.8555	0.8307	0.8804	-0.0044
c26	2	2	1	2	1	1	1	**0.9050**	0.8904	0.8683	0.9125	0.0147
c27	2	2	2	2	2	2	2	**0.9150**	0.9177	0.8982	0.9371	-0.0028

* Confidence interval for P: $\hat{p} \pm \mathrm{E} = \hat{p} \pm \mathrm{z} \times \sqrt{\frac{\hat{p}(1-\hat{p})}{N}}$

- For a 90 % confidence interval use z = 1.645
- For a 95 % confidence interval use z = 1.96
- For a 99 % confidence interval use z = 2.576
- *N*: the number of samples

[Case 2]

In the case of model B2, the utility values of car use can be estimated.

$$V_{car} = 0.3341 + (-0.3121)\cdot Park_j + (-0.3253)\cdot Congestion_j + (0.0186)\cdot Subsidy_j\cdot Park_j + (0.0189)\cdot Subsidy_j\cdot Congestion_j + (0.0213)\cdot Park_j\cdot Congestion_j + (0)\cdot Subsidy_j\cdot Park_j\cdot Congestion_j \quad \text{(Appendix 2-1)}$$

In the case of model B2, the monetary values of each level can be put into **Equation Appendix 2-1**. Since this model has been made up of the unit of 1,000 won, 2,211 won should be put into the equation as 2.211 whereas 2,500 won should be put into the equation as 2.5. The utility value of car use can be simply calculated by the method of substitution. For example, under the condition 14 (1 level → $Subsidy_j$: 1, $Park_j$: 1, $Congestion_j$: 1, 2 input value → $Subsidy_j$: 2.211, $Park_j$: 2.5, $Congestion_j$: 3) the deterministic part of the utility of car usage can be calculated as follows:

$$V_{car} = 0.3341 + (-0.3121)\cdot(2.5) + (-0.3253)\cdot(3) + (0.0186)\cdot(2.211)\cdot(2.5) + (0.0189)\cdot(2.211)\cdot(3) + (0.0213)\cdot(2.5)\cdot(3) + (0)\cdot(2.211)\cdot(2.5)\cdot(3) = -1.03412,$$

$$U_{car} = e^{-1.03412} = 0.35537 \quad \text{(Appendix 2-2)}$$

The utility value of car use is 0.35537.

Meanwhile, the utility of PT usage in model B2 can be calculated as follows. To get the maximum utility of the respondents of PT use, the maximizing values of MSP (β_1: 0.2015) are substituted into the utility of PT usage.

$$V_{PT} = \beta_1\cdot Subsidy_j = (0.2015)\cdot Subsidy_j = (0.2015)\cdot(2.211) = 0.445517,$$

$$U_{PT} = e^{0.445517} = 1.561296 \quad \text{(Appendix 2-3)}$$

The utility value of PT use is 1.561296.

$$P^i_{car} = \frac{e^{V_{i,car}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{e^{(-1.03412)}}{e^{(-1.03412)} + e^{(0.445517)}} = 0.185482 \cong 18.55\% \quad \text{(Appendix 2-4)}$$

$$P^i_{PT} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{e^{(0.445517)}}{e^{(-1.03412)} + e^{(0.445517)}} = 0.814518 \cong \mathbf{81.45\%} \quad \text{(Appendix 2-5)}$$

From the utility function, the estimated choice probability of car usage is 0.185482 whereas the estimated choice probability of PT usage is 0.814518.

Appendix Table 2-3 shows the observed choice probability and the estimated choice probability of travel mode in model B2. In addition, **Appendix Table 2-4** represents the market share of PT with respect to the change of level of MSPs (see blue coloured cell).

Appendix Table 2-3. The observed choice probability and estimated choice probability of travel mode in model B2

	Subsidy level	Parking Level	Congestion level	Observed probability of car	Utility Value of car	Utility Value of PT	Exponential utility value of car	Exponential utility value of PT	Market share rate of travel mode (%)	
									Car	PT
c1	0	0	0	0.7015	0.3341	0	1.396683	1	58.28	41.72
c2	0	0	3	0.4396	-0.6418	0	0.526344	1	34.48	65.52
c3	0	0	6	0.2166	-1.6177	0	0.198354	1	16.55	83.45
c4	0	2.5	0	0.4786	-0.44615	0	0.640088	1	39.03	60.97
c5	0	2.5	3	0.2636	-1.2623	0	0.283002	1	22.06	77.94
c6	0	2.5	6	0.1590	-2.07845	0	0.125124	1	11.12	88.88
c7	0	5	0	0.2988	-1.2264	0	0.293347	1	22.68	77.32
c8	0	5	3	0.1875	-1.8828	0	0.152163	1	13.21	86.79
c9	0	5	6	0.1277	-2.5392	0	0.07893	1	7.32	92.68
c10	2.211	0	0	0.4768	0.3341	0.445517	1.396683	1.561296	47.22	52.78
c11	2.211	0	3	0.3258	-0.51644	0.445517	0.596643	1.561296	27.65	72.35
c12	2.211	0	6	0.1694	-1.36697	0.445517	0.254877	1.561296	14.03	85.97
c13	2.211	2.5	0	0.3609	-0.34334	0.445517	0.709398	1.561296	31.24	68.76
c14	**2.211**	**2.5**	3	**0.1960**	**-1.03412**	0.445517	**0.363385**	1.561296	**18.55**	**81.45**
c15	2.211	2.5	6	0.1262	-1.78189	0.445517	0.178189	1.561296	10.24	89.76
c16	2.211	5	0	0.2174	-1.02078	0.445517	0.360315	1.561296	18.75	81.25
c17	2.211	5	3	0.1372	-1.55181	0.445517	0.211863	1.561296	11.95	88.05
c18	2.211	5	6	0.1052	-2.08285	0.445517	0.124575	1.561296	8.51	91.49
c19	4.422	0	0	0.3134	0.3341	0.891033	1.396683	2.437646	36.43	63.57
c20	4.422	0	3	0.2136	-0.39107	0.891033	0.676331	2.437646	21.72	78.28
c21	4.422	0	6	0.1117	-1.11625	0.891033	0.327507	2.437646	11.84	88.16
c22	4.422	2.5	0	0.2483	-0.24053	0.891033	0.786213	2.437646	24.39	75.61
c23	4.422	2.5	3	0.1352	-0.80595	0.891033	0.446664	2.437646	15.49	84.51
c24	4.422	2.5	6	0.0921	-1.37137	0.891033	0.253759	2.437646	9.43	90.57
c25	4.422	5	0	0.1489	-0.81515	0.891033	0.442571	2.437646	15.37	84.63
c26	4.422	5	3	0.0949	-1.22083	0.891033	0.294986	2.437646	10.79	89.21
c27	4.422	5	6	0.0851	-1.6265	0.891033	0.196617	2.437646	7.46	92.54

Appendix Table 2-4. The estimated market share of PT with respect to the change of level of MSPs

Type of Model	Level of policy	Commute cost subsidy	parking fee	Congestion charge	Subsidy& parking	Subsidy& Congestion	Parking& Congestion	Subsidy& Parking& Congestion
Model A0	0	40.36	40.36	40.36	40.36	40.36	40.36	40.36
	0.25	43.32	43.6	44.61	46.62	47.63	47.92	50.96
	0.5	46.33	46.9	48.94	52.98	55	55.57	61.47
	0.75	49.37	50.23	53.28	59.25	62.16	62.97	71.02
	1	52.41	53.55	57.58	65.23	68.83	69.81	79
	1.25	55.43	56.84	61.76	70.77	74.8	75.87	85.24
	1.5	58.41	60.08	65.78	75.75	79.96	81.04	89.87
	1.75	61.33	63.23	69.58	80.12	84.28	85.32	93.16
	2	64.18	66.26	73.13	83.87	87.81	88.76	95.44

Model B0	0	48.18	48.18	48.18	48.18	48.18	48.18	48.18
	0.25	49.83	51.76	52.79	53.4	54.43	56.34	57.95
	0.5	51.47	55.31	57.36	58.54	60.54	64.16	67.13
	0.75	53.12	58.81	61.8	63.5	66.34	71.3	75.16
	1	54.75	62.22	66.05	68.19	71.69	77.51	81.77
	1.25	56.38	65.52	70.06	72.53	76.48	82.7	86.92
	1.5	57.99	68.67	73.78	76.49	80.69	86.9	90.78
	1.75	59.58	71.66	77.19	80.04	84.29	90.2	93.59
	2	61.16	74.47	80.28	83.17	87.33	92.74	95.58
Model C0	0	42.54	42.54	42.54	42.54	42.54	42.54	42.54
	0.25	44.27	46.22	47.07	47.97	48.83	50.79	52.55
	0.5	46.02	49.94	51.65	53.45	55.16	59	62.36
	0.75	47.77	53.65	56.2	58.85	61.32	66.74	71.25
	1	49.53	57.33	60.65	64.04	67.14	73.66	78.76
	1.25	51.29	60.93	64.93	68.93	72.48	79.59	84.73
	1.5	53.05	64.41	68.98	73.42	77.24	84.46	89.25
	1.75	54.8	67.75	72.76	77.48	81.39	88.34	92.54
	2	56.54	70.92	76.24	81.08	84.94	91.35	94.89
Model A1	0	31.48	31.48	31.48	31.48	31.48	31.48	31.48
	0.25	35.74	36.17	37.71	40.42	41.57	41.97	46.11
	0.5	40.24	41.14	43.54	49.49	51.77	52.48	59.71
	0.75	44.91	46.3	49.97	58.04	61.21	62.07	70.61
	1	49.67	51.54	56.41	65.63	69.34	70.17	78.57
	1.25	54.43	56.75	62.64	72.06	75.96	76.65	84.13
	1.5	59.12	61.81	68.47	77.29	81.13	81.62	87.95
	1.75	63.65	66.63	73.78	81.46	85.08	85.36	90.6
	2	67.94	71.12	78.47	84.73	88.06	88.14	92.47
Model B1	0	41.29	41.29	41.29	41.29	41.29	41.29	41.29
	0.25	44.14	46.21	47.44	48.92	50.11	52.15	54.62
	0.5	47.03	51.2	53.66	56.21	58.47	62.26	66.1
	0.75	49.94	56.17	59.77	62.87	65.94	70.94	74.98
	1	52.85	61.02	65.6	68.74	72.32	77.93	81.42
	1.25	55.74	65.66	70.98	73.76	77.59	83.31	85.93
	1.5	58.59	70.02	75.84	77.96	81.82	87.33	89.06
	1.75	61.38	74.04	80.11	81.42	85.16	90.3	91.22
	2	64.1	77.7	83.79	84.23	87.78	92.47	92.72
Model C1	0	36.25	36.25	36.25	36.25	36.25	36.25	36.25
	0.25	38.82	41.41	41.91	43.86	44.48	46.92	49.32
	0.5	41.46	46.76	47.79	51.29	52.78	57.2	61.25
	0.75	44.14	52.19	53.73	58.2	60.7	66.26	71
	1	46.86	57.57	59.56	64.36	67.88	73.73	78.4
	1.25	49.6	62.77	65.14	69.68	74.12	79.58	83.82
	1.5	52.34	67.69	70.33	74.16	79.36	84.04	87.73
	1.75	55.06	72.25	75.05	77.86	83.64	87.36	90.55
	2	57.76	76.4	79.24	80.87	87.06	89.82	92.61
Model A2	0	32.45	32.45	32.45	32.45	32.45	32.45	32.45
	0.25	36.5	36.94	38.06	41.01	42.14	42.55	46.55
	0.5	40.75	41.66	44.01	49.75	52.01	52.73	59.84
	0.75	45.14	46.54	50.13	58.12	61.28	62.15	70.65
	1	49.61	51.49	56.25	65.7	69.41	70.25	78.59
	1.25	54.08	56.41	62.19	72.23	76.15	76.84	84.08
	1.5	58.49	61.2	67.78	77.66	81.51	82.01	87.77
	1.75	62.77	65.79	72.9	82.06	85.66	85.95	90.2
	2	66.85	70.1	77.48	85.55	88.82	88.91	91.77
Model B2	0	41.72	41.72	41.72	41.72	41.72	41.72	41.72
	0.25	44.45	46.53	47.75	49.15	50.34	52.37	54.79
	0.5	47.22	51.4	53.84	56.29	58.55	62.34	66.14

	0.75	50	56.24	59.82	62.89	65.96	70.95	75.01
	1	52.78	60.97	65.52	68.76	72.35	77.94	**81.45**
	1.25	55.55	65.5	70.8	73.84	77.67	83.36	85.96
	1.5	58.28	69.77	75.58	78.13	81.99	87.44	89.05
	1.75	60.96	73.72	79.8	81.7	85.44	90.46	91.14
	2	63.57	77.32	83.45	84.63	88.16	92.68	92.54
Model C2	0	39.62	39.62	39.62	39.62	39.62	39.62	39.62
	0.25	41.33	44.07	44.98	45.83	46.74	49.26	51.04
	0.5	43.07	48.62	50.45	52.17	54	58.42	61.82
	0.75	44.82	53.19	55.92	58.44	61.08	66.53	71.1
	1	46.58	57.71	61.24	64.45	67.73	73.35	**78.52**
	1.25	48.35	62.1	66.31	70.03	73.74	78.84	84.16
	1.5	50.12	66.3	71.03	75.08	78.97	83.15	88.31
	1.75	51.9	70.26	75.33	79.53	83.39	86.47	91.31
	2	53.67	73.94	79.18	83.36	87.04	89.01	93.46

[Case 3]

In the case of model C2, the utility values of car use can be estimated in the following way:

$$V_{car} = 0.4212 + (-0.2928)\cdot Park_j + (-0.3757)\cdot Congestion_j + (0)\cdot Subsidy_j\cdot Park_j + (0)\cdot Subsidy_j\cdot Congestion_j + (0.0303)\cdot Park_j\cdot Congestion_j + (0)\cdot Subsidy_j\cdot Park_j\cdot Congestion_j \quad \text{(Appendix 2-6)}$$

In the case of model C2, the monetary values of each level can be put into **Equation Appendix 2-6**. Since this model has been made up of the unit of 1,000 won, 2,211 won should be put into the equation as 2.211 whereas 2,500 won should be put into the equation as 2.5. The utility value of car use can be simply calculated by the method of substitution. For example, under the condition 14 (① level → $Subsidy_j$: 1, $Park_j$: 1, $Congestion_j$: 1, ② input value → $Subsidy_j$: 2.211, $Park_j$: 2.5, $Congestion_j$: 2.3387) the utility of car use can be calculated as follows:

$$V_{car} = 0.4212 + (-0.2928)\cdot(2.5) + (-0.3757)\cdot(2.3393) + (0)\cdot(2.211)\cdot(2.5) + (0)\cdot(2.211)\cdot(2.3387) + (0.0303)\cdot(2.5)\cdot(2.3387) = -1.01229,$$

$$U_{car} = e^{-1.01229} = 0.363385 \quad \text{(Appendix 2-7)}$$

The utility value of car use is 0.363385.

Meanwhile, the utility of PT use in model C2 can be calculated as follows. To get the maximum utility of the respondents of PT use, the maximizing values of the MSP (β_1: 0.1285) are substituted into the utility of PT use.

$$V_{PT} = \beta_1\cdot Subsidy_j = (0.1285)\cdot Subsidy_j = (0.1285)\cdot(2.211) = 0.284114,$$

$$V_{PT} = e^{0.284114} = 1.328584 \quad \text{(Appendix 2-8)}$$

The utility value of PT use is 1.328584.

$$P_{car}^{i} = \frac{e^{V_{i,car}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{e^{(-1.01229)}}{e^{(-1.01229)} + e^{(0.284114)}} = 0.214770 \cong 21.48\% \quad \text{(Appendix 2-9)}$$

$$P_{PT}^{i} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{e^{(0.284113)}}{e^{(-1.01229)} + e^{(0.284114)}} = 0.785230 \cong \mathbf{78.52\%}$$

$$\text{or } P_{PT}^{i} = 1 - P_{car}^{i} = 1 - 0.214770 = 0.785230 \cong \mathbf{78.52\%} \quad \text{(Appendix 2-10)}$$

From the utility function, the estimated choice probability of the car is 0.214770 whereas the estimated choice probability of PT is 0.785230 (see orange coloured cell in **Appendix Table 2-4** and blue coloured cell in **Appendix Table 2-5**). **Appendix Table 2-5** shows the observed choice probability and estimated the choice probability of travel mode in model C2.

Appendix Table 2-5. The observed choice probability and estimated choice probability of travel mode in model C2

	Subsidy level	Parking Level	Congestion level	Observed probability of car	Utility Value of car	Utility Value of PT	Exponential utility value of car	Exponential utility value of PT	Market share rate of travel mode	
									Car	PT
c1	0	0	0	0.7015	0.4212	0	1.523789	1	60.38	39.62
c2	0	0	2.3387	0.4396	-0.45745	0	0.632896	1	48.76	61.24
c3	0	0	4.6774	0.2166	-1.3361	0	0.262869	1	20.82	79.18
c4	0	2.5	0	0.4786	-0.3108	0	0.73286	1	42.29	57.71
c5	0	2.5	2.3387	0.2636	-1.01229	0	0.363385	1	26.65	73.35
c6	0	2.5	4.6774	0.1590	-1.71379	0	0.180182	1	15.27	84.73
c7	0	5	0	0.2988	-1.0428	0	0.352466	1	26.06	73.94
c8	0	5	2.3387	0.1875	-1.562163	0	0.156714	1	17.26	82.74
c9	0	5	4.6774	0.1277	-2.09147	0	0.123505	1	10.99	89.01
c10	2.211	0	0	0.4768	0.4212	0.284114	1.523789	1.328584	53.42	46.58
c11	2.211	0	2.3387	0.3258	-0.45745	0.284114	0.632896	1.328584	32.27	67.73
c12	2.211	0	4.6774	0.1694	-1.3361	0.284114	0.262869	1.328584	16.52	83.48
c13	2.211	2.5	0	0.3609	-0.3108	0.284114	0.73286	1.328584	35.55	64.45
c14	**2.211**	**2.5**	**2.3387**	**0.1960**	**-1.01229**	0.284114	**0.363385**	1.328584	**21.48**	**78.52**
c15	2.211	2.5	4.6774	0.1262	-1.71379	0.284114	0.180182	1.328584	11.94	88.06
c16	2.211	5	0	0.2174	-1.0428	0.284114	0.352466	1.328584	20.97	79.03
c17	2.211	5	2.3387	0.1372	-1.56714	0.284114	0.208642	1.328584	13.57	86.43
c18	2.211	5	4.6774	0.1052	-2.09147	0.284114	0.123505	1.328584	8.51	91.49
c19	4.422	0	0	0.3134	0.4212	0.568227	1.523789	1.765135	46.33	53.67
c20	4.422	0	2.3387	0.2136	-0.45745	0.568227	0.632896	1.765135	26.39	73.61
c21	4.422	0	4.6774	0.1117	-1.3361	0.568227	0.262869	1.765135	12.96	87.04
c22	4.422	2.5	0	0.2483	-0.3108	0.568227	0.73286	1.765135	29.34	70.66
c23	4.422	2.5	2.3387	0.1352	-1.01229	0.568227	0.363385	1.765135	17.07	82.93
c24	4.422	2.5	4.6774	0.0921	-1.71379	0.568227	0.180182	1.765135	9.26	90.74
c25	4.422	5	0	0.1489	-1.0428	0.568227	0.352466	1.765135	16.64	83.36
c26	4.422	5	2.3387	0.0949	-1.56714	0.568227	0.208642	1.765135	10.57	89.43
c27	4.422	5	4.6774	0.0851	-2.09147	0.568227	0.123505	1.765135	6.54	93.46

Appendix 3. Calculation of the Utility Value and the Choice Probability of Travel Mode under the Same Monetary Level of Policy Intervention

In the case of model A2, the utility values of car use can be estimated as follows:

$$\mathrm{U}_{car} = \mathrm{V}_{car} + \varepsilon_{\,car}$$

$$\mathrm{U}_{car} = \beta_0 + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \beta_{12} \cdot Subsidy_j \cdot Park_j + \beta_{13} \cdot Subsidy_j \cdot Congestion_j$$
$$+ \beta_{23} \cdot Park_j \cdot Congestion_j + \beta_{123} \cdot Subsidy_j \cdot Park_j \cdot Congestion_j + \varepsilon_{car}$$

$$\mathrm{V}_{car} = 0.7331 + (-0.7926) \cdot Park_j + (-0.9845) \cdot Congestion_j + (0.127) \cdot Subsidy_j \cdot Park_j$$
$$+ (0.1494) \cdot Subsidy_j \cdot Congestion_j + (0.1848) \cdot Park_j \cdot Congestion_j \qquad \text{(Appendix 3-1)}$$

In order to get the maximum utility of the respondents when using a car, the maximizing values of MSP (β_2, β_3, β_{12}, β_{13}, β_{23}, and β_{123}) are substituted into the utility of car use as in **Equation Appendix 3-1**. **Appendix Table 3-1** shows the input values of the same monetary level of policy intervention (1,000 won). In this case, suppose that 1,000 won (£0.56) is equally distributed into three MSPs. That is, for each MSP, values of 333 won (£0.19) are allocated. These values can be put into **Equation Appendix 3-1**.

Appendix Table 3-1. Input values of the same monetary level of policy intervention

Classifi-cation	Type of Model	Subsidy	Parking	Congestion	Subsidy & Parking		Subsidy & Congestion		Parking & Congestion		Subsidy & Parking & congestion		
					subsidy	Parking	subsidy	Conges-tion	Parking	Conges-tion	Subsidy	parking	Conges-tion
1,000 won (£ 0.56)	Models A	0.45228403	0.4	0.33333	0.2260398	0.2	0.22614201	0.166666	0.2	0.166666	0.15076134	0.1333333	0.111111
	Models B	1	1	1	0.5	0.5	0.5	0.5	0.5	0.5	0.333333	0.333333	0.333333
	Models C	1	1	0.7795667	0.5	0.5	0.5	0.3897833	0.5	0.3897833	0.333333	0.333333	0.2598556

* Since models A, using only SP data from the survey, are based on the level unit, transformation of the input value should be calculated: 0.45228403 (level) = 1,000/2,211 (won), 0.4 (level) = 1,000/2,500 (won), 0.333333 (level) = 1,000/3,000 (won), 0.22614201 (level) = 0.45228403 X (1/2) (level) (=1,000/2,211 X (1/2) won), 0.2 (level) = 0.4 X (1/2) (level), 0.1666666(level) = 0.333333 X (1/2) (level), 0.15076134 (level) = 0.45228403 X (1/3) (level), 0.1333333 (level) = 0.4 X (1/3) (level), 0.111111(level) = 0.333333 X (1/3) (level)

* Since models B, using SP data and RP data from the survey, are based on the money unit, the transformation is not needed. In models B, 1 equates with 1,000 won. Therefore, 0.5 equals 500 won (=1,000 X (1/2) won), 0.333333 equals 333 won (=1,000 X (1/3) won)

* Since models C, using SP data and RP data from the survey, are also based on the money unit, the transformation is not needed. However, models C should be reflected by reduced commuting time effect of congestion charging. In the survey questionnaire, if congestion charging is introduced at level one (levy on 3,000 won), a 10% reduction in total travel time is assumed. In addition, if the congestion charging is introduced at level two (levy on 6,000 won), a 20% reduction in total travel

time is assumed. Therefore, as for the level one, reduced commuting time effect of congestion charging is calculated by 661.27 won from RP data as self-reported data in the survey. In addition, as in level two of congestion charges, 1,322.53 was calculated as the average monetary value of a 20% reduction in total travel time. In models C, 1 equates with 1,000 won. Therefore, 0.7795667 equals 779 won (= 2,339 X (1/3) won) derived from average time value of 10% reduction in total time due to implementation of congestion charging [3,000 won – 661.27 won = 2,339 won]. 0.3897833 equals 389 won (=0.7795667 X (1/2) won). 0.2598556 equals 259 won (=0.7795667 X (1/3) won).

The method of substitution can simply calculate the utility value of the car use. Under the economic condition at the level of 1,000 won (*Subsidy*$_j$*:* 333 won, *Park*$_j$: 333 won, *Congestion*$_j$: 333 won, input value: *Subsidy*$_j$: 0.15076134, *Park*$_j$: 0.1333333, *Congestion*$_j$: 0.111111), the utility of car use can be calculated as follows:

$$V_{car} = 0.7331 + (-0.7926)\cdot(0.133333) + (-0.9845)\cdot(0.111111) + (0.127)\cdot(0.15069318)\cdot(0.133333) + (0.1494)\cdot(0.15076134)\cdot(0.1111111) + (0.1848)\cdot(0.1333333)\cdot(0.111111) = 0.525824,$$

$$U_{car} = e^{0.525824} = 1.691853 \qquad \text{(Appendix 3-2)}$$

The utility value of car use is 1.691853.

Meanwhile, the utility values of PT use in model A2 can be estimated. To get the maximum utility of the respondents with PT use, the maximizing values of MSP (β_1: 0.7173) are substituted into the utility of PT use as in **Equation Appendix 3-3**.

$$V_{PT} = \beta_1 \cdot Subsidy_j = (0.7173)\cdot(0.15076134) = 0.108141,$$

$$U_{PT} = e^{0.108141} = 1.114205 \qquad \text{(Appendix 3-3)}$$

The utility value of PT is 1.114205.

$$P^i_{car} = \frac{e^{V_{i,car}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{e^{(0.525824)}}{e^{(0.525824)} + e^{(0.108141)}} = 0.602929 \cong 60.29\% \qquad \text{(Appendix 3-4)}$$

$$P^i_{PT} = \frac{e^{V_{i,PT}}}{e^{V_{i,car}} + e^{V_{i,PT}}} = \frac{e^{(0.108141)}}{e^{(0.525824)} + e^{(0.108141)}} = 0.397067 \cong \mathbf{39.71\%}$$

$$\text{or } P^i_{PT} = 1 - P^i_{car} = 1 - 0.602929 = 0.397067 \cong \mathbf{39.71\%} \qquad \text{(Appendix 3-5)}$$

From the utility function, the estimated choice probability of car is 0.602929 whereas the estimated choice probability of PT is 0.397067 (see the blue coloured cell in **Appendix Table 3-2**).

Appendix Table 3-2 compares the market share of PT in respect to the individual MSP and the combined MSPs at the same monetary level of policy intervention.

Appendix Table 3-2. Comparison of the market share of PT in relation to MSPs at the same monetary level of policy intervention (%)

Economic differences	Type of model	Commute cost subsidy	parking fee	Congestion charge	Subsidy& parking	Subsidy& Congestion	Parking& Congestion	Subsidy& Parking& congestion
1,000 won (£ 0.56)	Model A0	45.75	45.58	46.04	45.66	45.90	45.81	45.79
	Model B0	51.16	53.89	54.32	52.53	52.74	54.11	53.13
	Model C0	45.68	48.45	48.60	47.06	47.14	48.52	47.57
	Model A1	39.36	39.13	39.35	39.05	39.17	39.05	39.03
	Model B1	46.68	49.20	49.51	47.70	47.85	49.20	48.20
	Model C1	40.95	44.60	43.85	42.60	42.32	44.04	42.94
	Model A2	39.92	39.75	40.01	39.70	39.83	39.73	**39.71**
	Model B2	46.69	49.45	49.78	47.95	48.12	49.48	48.48
	Model C2	42.73	46.79	46.80	44.76	44.76	46.65	45.37
2,000 won (£ 1.11)	Model A0	51.24	50.89	51.84	51.07	51.54	51.36	51.32
	Model B0	54.13	59.50	60.34	56.83	57.26	59.92	58.01
	Model C0	48.86	54.39	54.69	51.63	51.78	54.54	52.66
	Model A1	47.84	47.35	47.82	46.78	47.05	46.78	46.64
	Model B1	51.74	57.15	57.76	53.89	54.20	56.86	54.81
	Model C1	45.82	53.27	51.76	48.85	48.49	51.77	49.53
	Model A2	47.89	47.53	48.08	47.13	47.42	47.19	47.05
	Model B2	51.72	57.20	57.85	54.01	54.33	57.00	54.96
	Model C2	45.90	54.10	54.11	50.00	50.01	53.52	51.11
3,000 won (£ 1.67)	Model A0	56.70	56.19	57.58	56.45	57.14	56.88	56.82
	Model B0	57.07	64.87	66.05	61.04	61.66	65.46	62.74
	Model C0	52.05	60.22	60.65	56.17	56.40	60.44	57.68
	Model A1	56.44	55.71	56.41	54.27	54.70	54.27	53.92
	Model B1	56.96	64.75	65.60	59.70	60.15	63.91	60.89
	Model C1	50.77	61.75	59.57	54.80	54.56	59.04	55.79
	Model A2	55.96	55.43	56.25	54.42	54.86	54.47	54.15
	Model B2	56.72	64.62	65.52	59.74	60.19	63.97	60.97
	Model C2	49.11	61.23	61.25	55.25	55.26	59.97	56.70
4,000 won (£ 2.22)	Model A0	62.01	61.35	63.12	61.68	62.56	62.24	62.16
	Model B0	59.96	69.89	71.33	65.09	65.87	70.62	67.24
	Model C0	55.22	65.77	66.31	60.62	60.90	66.04	62.56
	Model A1	64.67	63.77	64.63	61.19	61.77	61.19	60.59
	Model B1	62.03	71.67	72.67	64.98	65.55	70.16	66.33
	Model C1	55.70	69.57	66.93	60.29	60.35	65.61	61.56
	Model A2	63.74	63.07	64.10	61.25	61.82	61.27	60.70
	Model B2	61.58	71.39	72.45	64.99	65.56	70.17	66.37
	Model C2	52.32	67.92	67.93	60.38	60.39	65.83	61.99
5,000 won (£ 2.78)	Model A0	67.04	66.26	68.34	66.65	67.69	67.31	67.22
	Model B0	62.78	74.47	76.09	68.93	69.85	75.29	71.45
	Model C0	58.34	70.92	71.54	64.89	65.23	71.23	67.19
	Model A1	72.12	71.12	72.08	67.33	68.03	67.33	66.49
	Model B1	66.85	77.70	78.75	69.69	70.35	75.51	71.09
	Model C1	60.53	76.40	73.54	65.21	65.74	71.32	66.73
	Model A2	70.85	70.10	71.25	67.41	68.08	67.39	66.55
	Model B2	66.23	77.32	78.46	69.71	70.37	75.52	71.11
	Model C2	55.51	73.94	73.95	65.30	65.30	71.00	66.90
6,000 won (£ 3.33)	Model A0	71.71	70.85	73.13	71.28	72.42	72.01	71.91
	Model B0	65.52	78.58	80.28	72.53	73.55	79.44	75.31
	Model C0	61.41	75.58	76.24	68.94	69.32	75.91	71.51
	Model A1	78.51	77.50	78.47	72.61	73.40	72.61	71.58
	Model B1	71.35	82.75	83.79	73.79	74.52	79.98	75.16
	Model C1	65.16	82.09	79.24	69.54	70.63	76.15	71.28
	Model A2	77.08	76.30	77.48	72.79	73.53	72.73	71.61
	Model B2	70.58	82.32	83.45	73.87	74.58	80.00	75.18
	Model C2	58.66	79.18	79.19	69.90	69.91	75.46	71.36

* 0 won: model A0 (40.36), model A1 (31.48), model A2 (32.45), model B0 (48.18), model B1 (41.29), model B2 (41.72), model C0 (42.54), model C1 (36.25), model C2 (39.62)

Appendix 4. Estimation Results of the Mixed Logit Models with Uniform Distribution

	Coefficient	beta	Value	t-value	Goodness of fit
Model A0	**ASC**	$\boldsymbol{\beta_0}$	**0.7064**	**10.7008****	L(0) = - 14035.5 L(β) = - 10048 ρ^2 = 0.284 Number of observations : 767
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.7536**	**-10.8251****	
	Random effect (SD)		**1.1420**	**5.6112****	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.8472**	**-11.4914****	
	Random effect (SD)		**1.2580**	**6.4889****	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-1.0362**	**-13.0718****	
	Random effect (SD)		**1.1582**	**5.9566****	
Model B0	**ASC**	$\boldsymbol{\beta_0}$	**0.6327**	**9.3476****	L(0) = - 12405.3 L(β) = - 8242.1 ρ^2 = 0.336 Number of observations : 678
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.5146**	**-11.3621****	
	Random effect (SD)		**0.8875**	**10.4264****	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.3687**	**-10.9716****	
	Random effect (SD)		**0.4869**	**5.6605****	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-0.3706**	**-12.4593****	
	Random effect (SD)		**0.3629**	**4.9553****	
Model C0	**ASC**	$\boldsymbol{\beta_0}$	**1.0772**	**12.7796****	L(0) = - 10704.3 L(β) = - 7553.5 ρ^2 = 0.294 Number of observations : 582
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.5812**	**-11.3466****	
	Random effect (SD)		**1.0271**	**10.0433****	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.4184**	**-11.2846****	
	Random effect (SD)		**0.5205**	**5.1226****	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-0.6281**	**-12.7741****	
	Random effect (SD)		**0.8405**	**8.7705****	
Model A1	**ASC**	$\boldsymbol{\beta_0}$	**0.7795**	**12.5081****	L(0) = - 14035.5 L(β) = - 10020 ρ^2 = 0.286 Number of observations : 767
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.7682**	**-13.5639****	
	Random effect (SD)		-0.1466	-0.1713	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.8254**	**-13.9883****	
	Random effect (SD)		-0.1329	-0.1538	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-1.0209**	**-17.1744****	
	Random effect (SD)		-0.1069	-0.1423	
	Subsidy & Parking (mean)	$\boldsymbol{\beta_{12}}$	**0.1791**	**4.1396****	
	Random effect (SD)		-0.0037	-0.0046	
	Subsidy & Congestion (mean)	$\boldsymbol{\beta_{13}}$	**0.2065**	**4.5590****	
	Random effect (SD)		-0.0101	-0.0222	
	Parking & Congestion (mean)	β_{23}	0.1126	1.5608	
	Random effect (SD)		**0.5748**	**4.0381****	
	Subsidy & Parking & Congestion (mean)	β_{123}	-0.0822	-1.5719	
	Random effect (SD)		0.1056	0.4495	
Model B1	**ASC**	$\boldsymbol{\beta_0}$	**0.6238**	**8.8295****	L(0) = - 12405.3 L(β) = - 8232 ρ^2 = 0.336 Number of observations: 678
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.4730**	**-11.0950****	
	Random effect (SD)		**0.8049**	**9.0159****	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.3339**	**-9.8041****	
	Random effect (SD)		0.1996	1.1974	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-0.3473**	**-11.1494****	
	Random effect (SD)		0.1818	1.5254	
	Subsidy & Parking (mean)	β_{12}	-0.0012	-0.1101	
	Random effect (SD)		0.0051	0.0547	
	Subsidy & Congestion (mean)	β_{13}	-0.0020	-0.2056	
	Random effect (SD)		-0.0083	-0.1190	
	Parking & Congestion (mean)	β_{23}	0.0067	0.6102	
	Random effect (SD)		**0.0807**	**3.5299****	
	Subsidy & Parking & Congestion (mean)	β_{123}	0.0010	0.3249	
	Random effect (SD)		0.0014	0.0719	

Model C1	**ASC**	$\boldsymbol{\beta_0}$	**1.0601**	**12.2806****	L(0) = - 10704.3 L(β) = - 7546 ρ^2 = 0.295 Number of observations: 582
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.5427**	**-10.7136****	
	Random effect (SD)		**0.9821**	**8.4582****	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.3974**	**-10.3791****	
	Random effect (SD)		**0.3203**	**2.2821***	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-0.5847**	**-11.6187****	
	Random effect (SD)		**0.6547**	**6.2121****	
	Subsidy & Parking (mean)	β_{12}	-0.0022	-0.1604	
	Random effect (SD)		0.0163	0.2147	
	Subsidy & Congestion (mean)	β_{13}	-0.0093	-0.5180	
	Random effect (SD)		0.0477	0.5490	
	Parking & Congestion (mean)	β_{23}	0.0022	0.1232	
	Random effect (SD)		**0.1437**	**3.6437****	
	Subsidy & Parking & Congestion (mean)	β_{123}	0.0000	-0.0074	
	Random effect (SD)		-0.0109	-0.4258	
Model A2	**ASC**	$\boldsymbol{\beta_0}$	**0.7417**	**11.9716****	L(0) = - 14035.5 L(β) = - 10022 ρ^2 = 0.286 Number of observations: 767
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.7360**	**-12.6762****	
	Random effect (SD)		-0.3974	-1.0782	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.7782**	**-13.7626****	
	Random effect (SD)		-0.1325	-0.1505	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-0.9765**	**-14.8256****	
	Random effect (SD)		0.2261	0.4109	
	Subsidy & Parking (mean)	$\boldsymbol{\beta_{12}}$	**0.1171**	**3.5992****	
	Random effect (SD)		0.0199	0.0257	
	Subsidy & Congestion (mean)	$\boldsymbol{\beta_{13}}$	**0.1373**	**4.2235****	
	Random effect (SD)		-0.0196	-0.0418	
	Parking & Congestion (mean)	β_{23}	0.0530	0.8711	
	Random effect (SD)		**0.5685**	**4.3739****	
Model B2	**ASC**	$\boldsymbol{\beta_0}$	**0.6464**	**9.3113****	L(0) = - 12405.3 L(β) = - 8231.2 ρ^2 = 0.336 Number of observations: 678
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.4850**	**-11.4415****	
	Random effect (SD)		**0.8230**	**9.1823****	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.3452**	**-10.1506****	
	Random effect (SD)		0.2353	1.5945	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-0.3638**	**-11.6684****	
	Random effect (SD)		**-0.2392**	**-2.4345***	
	Subsidy & Parking (mean)	β_{12}	0.0006	0.0773	
	Random effect (SD)		0.0122	0.1268	
	Subsidy & Congestion (mean)	β_{13}	-0.0005	-0.0769	
	Random effect (SD)		-0.0011	-0.0173	
	Parking & Congestion (mean)	β_{23}	0.0106	1.0549	
	Random effect (SD)		**-0.0431**	**-2.8432****	
Model C2	**ASC**	$\boldsymbol{\beta_0}$	**0.9091**	**12.2042****	L(0) = - 10704.3 L(β) = - 7553.8 ρ^2 = 0.294 Number of observations: 767
	PT commute cost subsidy (mean)	$\boldsymbol{\beta_1}$	**-0.4768**	**-11.5669****	
	Random effect (SD)		**0.8245**	**10.2878****	
	Additional parking fee (mean)	$\boldsymbol{\beta_2}$	**-0.3417**	**-12.5599****	
	Random effect (SD)		-0.0714	-0.1957	
	Congestion charge (mean)	$\boldsymbol{\beta_3}$	**-0.4444**	**-12.5873****	
	Random effect (SD)		0.1252	0.5253	
	Parking & Congestion (mean)	β_{23}	-0.0170	-1.0411	
	Random effect (SD)		**0.1807**	**6.3746****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Appendix 5. Calculation of the Choice Probability of Travel Mode in the Mixed Logit Models

1. The calculation method using estimated mean parameter

In the case of model A0, the utility values of car use can be estimated. The utility function using integrated model A0 is as follows:

$$U_{car} - U_{PT} = \beta_0 - \beta_1 \cdot Subsidy_j + \beta_2 \cdot Park_j + \beta_3 \cdot Congestion_j + \varepsilon_{car} - \varepsilon_{PT}$$

$$V_{car} - V_{PT} = 0.76834 - (0.80291) \cdot Subsidy_j + (-0.90433) \cdot Park_j + (-1.10127) \cdot Congestion_j$$

In **Appendix Table 5-1**, coefficients related to the main effect variables (means) can be used to obtain the utility values of car usage. The utility values of car use can be calculated by the substitution method. In this case, V_{PT} is assumed as zero to easily calculate the choice probability of travel mode.

Appendix Table 5-1. Coefficient and statistical values of the MLM (model A0)

Type of model	Coefficient	Beta	Value	t-value	Goodness of fit of the statistics
Mixed logit model (Model A0)	**ASC**	β_0	**0.7683**	**11.2896****	L(0) = - 14035.5 L(β) = - 10044 ρ^2 = 0.284 Number of observations: 767
	PT commute cost subsidy (Mean)	β_1	**0.8029**	**11.3520****	
	Random effect (SD)		**0.7521**	**5.9349****	
	Additional parking fee (Mean)	β_2	**-0.9043**	**-12.0274****	
	Random effect (SD)		**0.8334**	**6.8120****	
	Congestion charge (Mean)	β_3	**-1.1013**	**-13.4137****	
	Random effect (SD)		**0.7606**	**6.2012****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

For example, under the condition 19 (input value: $Subsidy_j$: 2; $Park_j$: 0; $Congestion_j$: 0), the deterministic part of the utility of car use can be calculated as follows:

$$V_{car} = 0.76834 - (0.80291) \cdot (2) + (-0.90433) \cdot (0) + (-1.10127) \cdot (0) = -0.83748$$

$$U_{car} = e^{-0.83748} = 0.43280$$

The utility value of car use is 0.43280.

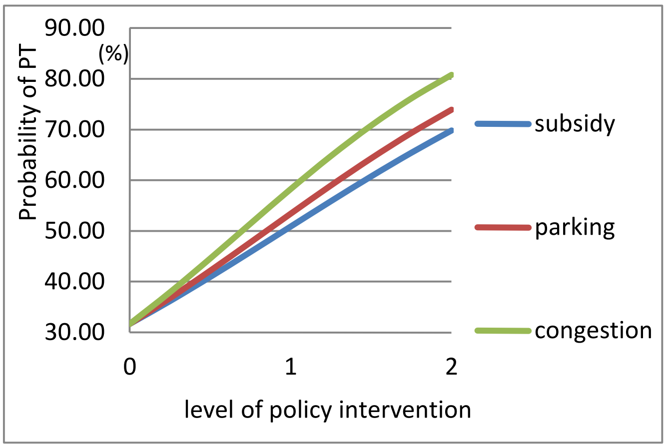
$$P^i_{car} = \frac{1}{1 + \{1/\exp\left(V_{i,j,car}\right)\}} = \frac{1}{1 + \{1/\exp\left(-0.83748\right)\}} = 0.302066 \cong \mathbf{30.21\%}$$

$$P^i_{PT} = 1 - P^i_{car} = 1 - 0.302066 = 0.697934 \cong \mathbf{69.79\%}$$

From the utility function, the estimated choice probability of car is 0.302066 whereas the estimated choice probability of PT is 0.697934. Through choice probability of PT, the modal shift probability curve can be obtained as in **Appendix Table 5-2**.

Appendix Table 5-2. Choice probability of PT from the fixed effect coefficient (mean) of the MLM

Type of model	Commute cost subsidy	parking fee	Congestion charge
0	31.68	31.68	31.68
0.25	36.18	36.77	37.92
0.5	40.93	42.16	44.58
0.75	45.86	47.75	51.44
1	50.86	53.39	58.25
1.25	55.86	58.95	64.75
1.5	60.73	64.29	70.76
1.75	65.40	69.30	76.11
2	**69.79**	73.89	80.76



2. The calculation method using random effect variables

The standard deviation of MSP can be gained by the formula $\sigma_x = \frac{\sigma}{\sqrt{n}}$ (σ: value of random effect coefficient, *n*: number of samples). The standard deviation of the PT commuting cost subsidy is $\frac{0.752054}{\sqrt{767}}$ = 0.0271551, additional parking fee $\frac{0.833437}{\sqrt{767}}$ = 0.03000937, and congestion charge $\frac{0.76056}{\sqrt{767}}$ = 0.0274622.

In the normal distribution, the upper and lower bounds of a 5% confidence interval are $\pm$1.96. Thus, if the mean is 0 and variance is 1, the confidence interval at the level of 95% is 0 $\pm$1.96*standard error ($\sqrt{variance/n}$).

The random effect value can be added to the deterministic part of car use. The utility value of travel mode can be obtained within the confidence interval of random effect at the level of 95 % using the following:

* 95% high value: V_{car} = 0.76834 – (0.80291)·(2) + (– 0.90433)·(0) + (– 1.10127)·(0)

= – 0.83748 **+ (1.96)*0.752054/$\sqrt{767}$** = – 0.784260

$U_{car} = e^{-0.784260}$ = 0.45645735

$P^i_{car} = \frac{1}{1+\{1/\exp\left(V_{i,j,car}\right)\}} = \frac{1}{1+\{1/\exp(-0.784260)\}}$ = 0.31340248 ≅ **31.34%**

$P^i_{PT} = 1 - P^i_{car}$ = 1 – 0.31340248 = 0.686598 ≅ **68.66%**

* 95% low value: $V_{car} = 0.76834 - (0.80291)\cdot(2) + (-0.90433)\cdot(0) + (-1.10127)\cdot(0)$

$$= -0.83748 - (1.96)*0.752054/\sqrt{767} = -0.890708$$

$$U_{car} = e^{-0.890708} = 0.41036512$$

$$P^{i}_{car} = \frac{1}{1+\{1/\exp\left(V_{i,j,car}\right)\}} = \frac{1}{1+\{1/\exp(-0.890708)\}} = 0.29096375 \cong \mathbf{29.10\%}$$

$$P^{i}_{PT} = 1 - P^{i}_{car} = 1 - 0.29096375 = 0.709036 \cong \mathbf{70.90\%}$$

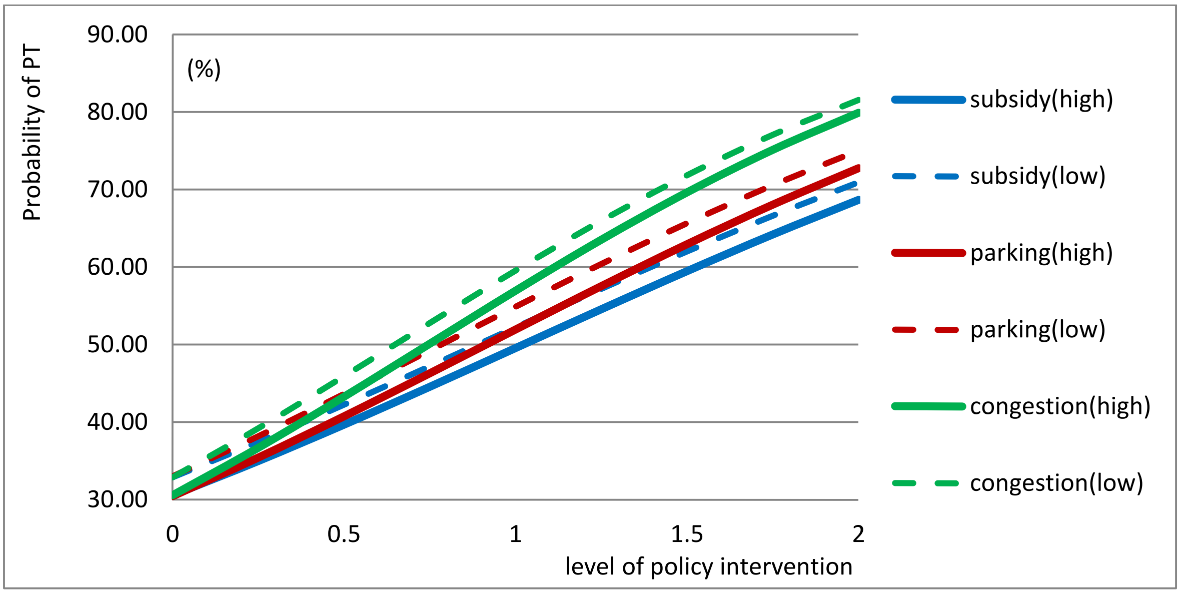
Appendix Table 5-3 and **Appendix Figure 5-1** show the maximum and the minimum choice probability of PT using the random effect variables in the MLM. The real choice probability of travel mode will be determined between the maximum value and the minimum value.

Appendix Table 5-3. Maximum and minimum choice probability of PT using the random effect variables in the MLM

Type of model	PT Commute cost subsidy		Additional parking fee		Congestion charge	
	High	Low	High	Low	High	low
0	30.54	32.85	30.42	32.97	30.53	32.86
0.25	34.96	37.42	35.41	38.15	36.66	39.19
0.5	39.65	42.22	40.73	43.61	43.25	45.91
0.75	44.54	47.18	46.28	49.22	50.09	52.78
1	49.53	52.19	51.92	54.86	56.93	59.55
1.25	54.54	57.16	57.52	60.37	63.52	65.97
1.5	59.45	61.99	62.93	65.64	69.63	71.86
1.75	64.19	66.60	68.03	70.54	75.12	77.08
2	**68.65**	**70.92**	72.74	75.01	79.91	81.58

* There are the difference between the values (68.66, 70.90) in the above calculation and the values (68.65, 70.92) in this Table. Therefore, it may be a round off problem.

Appendix Figure 5-1. Maximum and minimum choice probability of PT using the random effect variables in the MLM



At the same time, the random numbers can be used to predict the realistic and particular choice probability of travel mode. For example, five random numbers are arbitrarily obtained from the normal distribution. In general, the random number cannot exceed the critical value. The random number can be obtained by R programme (rnorm(5, 0, sd=0.752054/sqrt(767)).

0.01653284 0.03122852 – 0.03257519 – 0.04290507 0.01773679

Out of five random numbers, any random number can be arbitrarily selected by the researcher. The utility function of the car use is calculated as follows:

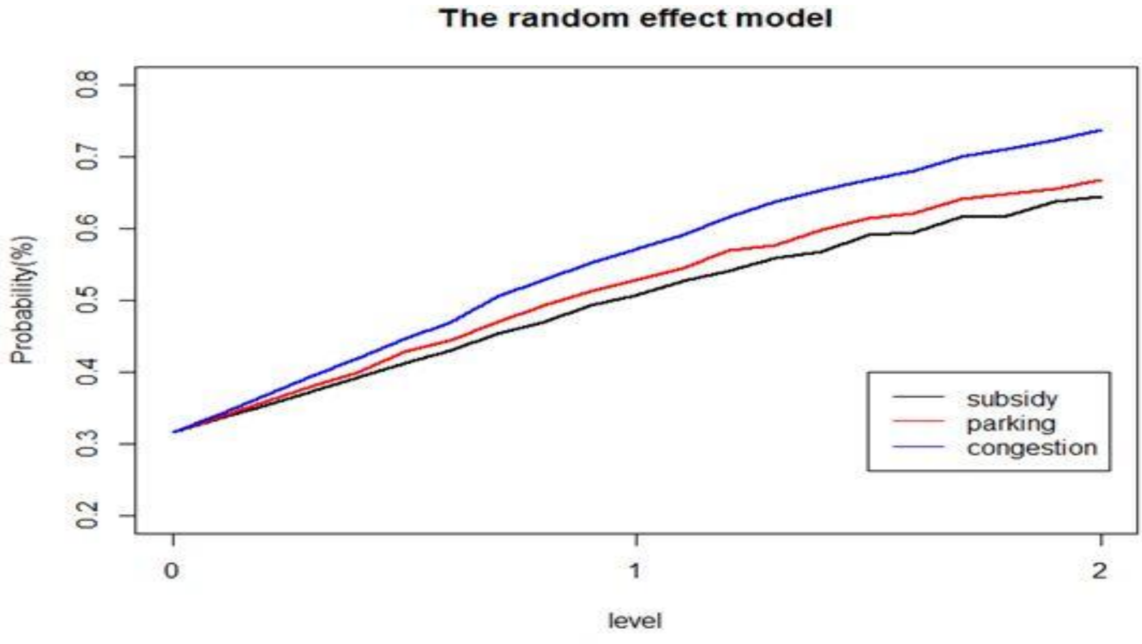
$V_{car} = 0.76834 - (0.80291)\cdot(2) + (-0.90433)\cdot(0) + (-1.10127)\cdot(0) = -0.83748 + 0.01653284$
$= -0.82095$
$U_{car} = e^{-0.82095} = 0.440013$

The utility value of car use is 0.440013.

$P^{i}_{car} = \frac{1}{1+\{1/\exp\left(V_{i,j,car}\right)\}} = \frac{1}{1+\{1/\exp(-0.82095)\}} = 0.305562 \cong$ **30.56%**

$P^{i}_{PT} = 1 - P^{i}_{car} = 1 - 0.305562 = 0.694438 \cong$ **69.44%**

Appendix Figure 5-2. Concept map for the choice probability of PT using the random effect variable in the MLM (Conditional simulation)



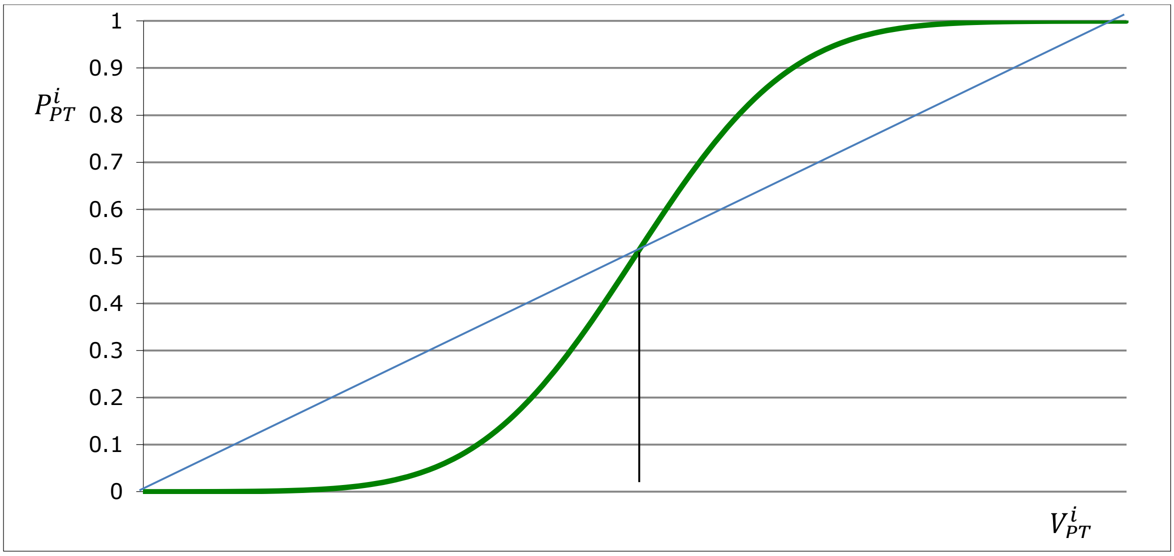
As can be seen in **Appendix Figure 5-2**, due to the influence of random effects, the choice probability of travel mode is fluctuated. All in all, since the MLM focuses on the introduction of flexible variations, the MLM has a limitation in exactly and precisely predicting the choice probability of travel mode.

Appendix 6. Detailed Result of the Analysis for Models with No Coefficient Related to Interaction Effects

In the case of no interaction effect, the modal shift synergy effect should be 0 in terms of common sense. However, as shown in **Appendix Table 6-1**, the analytical result of models having no statistically significant coefficient related to interaction effects shows the real data value. That is, the values of modal shift synergy effect show positive values, not zero. As shown in **Appendix Figure 6-2** and **Appendix Figure 6-3**, the positive values of the modal shift synergy effect show consistent and regular patterns. What is the cause of the positive modal shift synergy effect?

As shown in **Appendix Figure 6-1**, the graph of the logit curve is S-shaped. That is, since the relationship between the choice probability of PT and the deterministic utility represents an S-shaped curve, the differences of the choice probability of PT between the S-shaped curve and straight line might be created. Since the calculation of the modal shift synergy effect is based on the choice probability of PT, the modal shift synergy effect of the combined MSPs might represent positive values. If the logit curve takes the form of a straight line, there would be no modal shift synergy effects in the model having no significant coefficient in terms of statistics. In conclusion, the occurrence of deviations may derive from the form of logit curve significantly.

Appendix Figure 6-1. Graph of logit curve



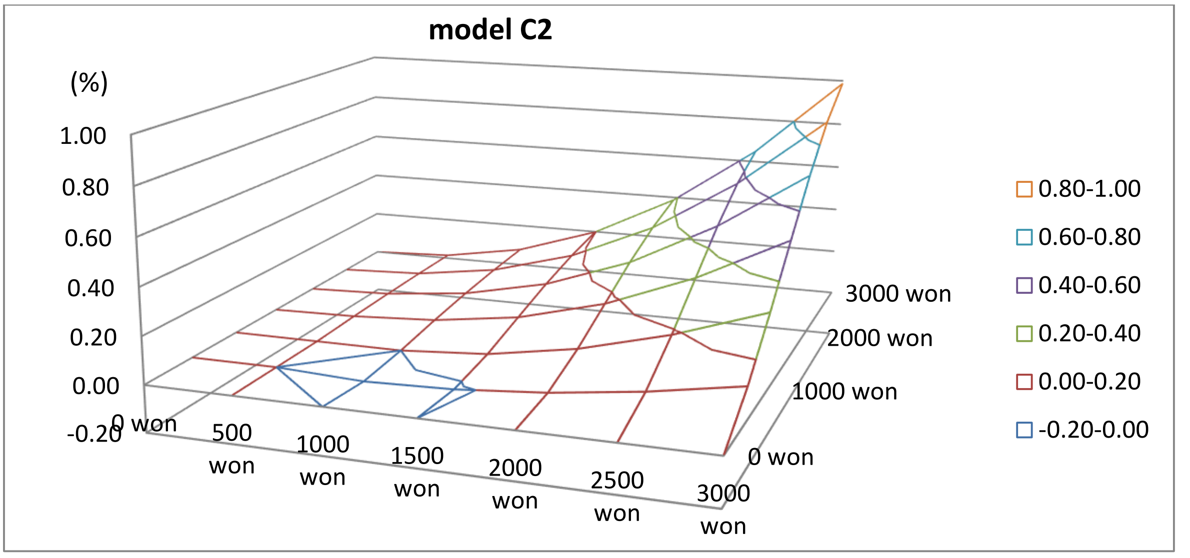
*Source: adopted from Train, 2003.

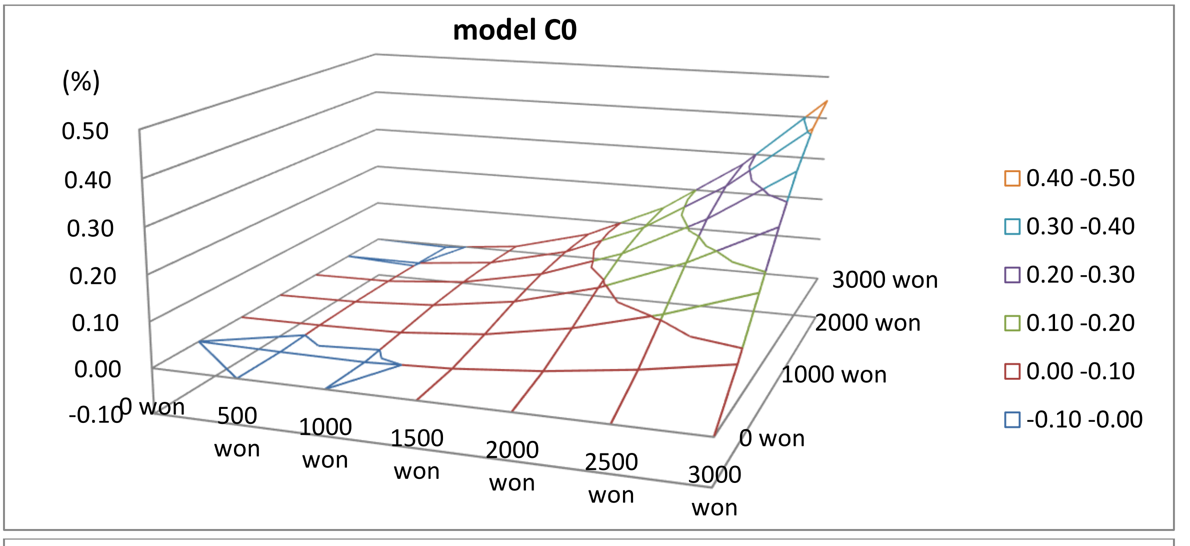
However, in a comparison of **Appendix Table 6-1** and **Appendix Table 6-2**, the magnitude of the modal shift synergy effect does not depend entirely on the magnitude of the choice probability of PT. That is, in comparison of the different types of models (e.g. model C2 and model B0), the magnitude of the modal shift synergy effect of the combined MSPs does not correspond to the choice probability of the travel mode. Therefore, the reason for the occurrence of the deviations between these two values cannot be explained only by the shape of the logit curve. Thus, more consideration and research is required.

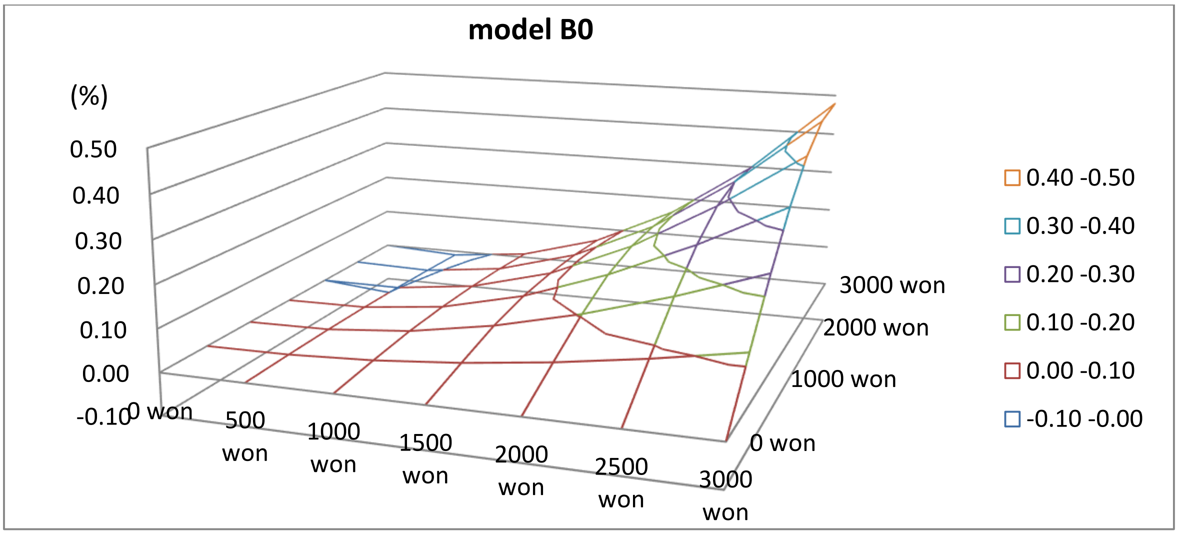
Appendix Table 6-1. The modal shift synergy effects of the combined MSPs in accordance with the change of the magnitude of policy intervention

	parking \ subsidy	0 won	500 won	1000 won	1500 won	2000 won	2500 won	3000 won
PT commuting cost subsidy + additional parking fee								
Model C2	0 won	0	0	0	0	0	0	0
	500 won	0	0.00	-0.02	-0.01	0.02	0.07	0.14
	1000 won	0	0.00	0.00	0.03	0.09	0.19	0.32
	1500 won	0	0.01	0.03	0.08	0.18	0.32	0.52
	2000 won	0	0.01	0.05	0.13	0.26	0.46	0.71
	2500 won	0	0.01	0.07	0.17	0.34	0.57	0.87
	3000 won	0	0.01	0.08	0.20	0.39	0.65	0.99
Model C0	0 won	0	0	0	0	0	0	0
	500 won	0	0.00	0.00	0.00	0.02	0.05	0.08
	1000 won	0	0.00	0.01	0.02	0.06	0.11	0.17
	1500 won	0	0.00	0.01	0.04	0.09	0.17	0.26
	2000 won	0	0.00	0.02	0.06	0.12	0.22	0.35
	2500 won	0	0.00	0.02	0.06	0.14	0.26	0.41
	3000 won	0	-0.01	0.01	0.06	0.15	0.27	0.44
Model B0	0 won	0	0	0	0	0	0	0
	500 won	0	0.00	0.01	0.03	0.05	0.08	0.12
	1000 won	0	0.00	0.02	0.05	0.10	0.16	0.24
	1500 won	0	0.00	0.02	0.07	0.14	0.23	0.34
	2000 won	0	0.00	0.02	0.08	0.16	0.28	0.42
	2500 won	0	-0.01	0.02	0.07	0.17	0.30	0.47
	3000 won	0	-0.01	0.01	0.07	0.16	0.30	0.48
PT commuting cost subsidy + congestion charge								
	congestion \ subsidy	0 won	500 won	1000 won	1500 won	2000 won	2500 won	3000 won
Model C2	0 won	0	0	0	0	0	0	0
	500 won	0	-0.01	-0.02	-0.01	0.02	0.07	0.14
	1000 won	0	0.00	0.00	0.03	0.09	0.19	0.32
	1500 won	0	0.01	0.03	0.08	0.18	0.32	0.52
	2000 won	0	0.01	0.05	0.13	0.26	0.46	0.71
	2500 won	0	0.01	0.07	0.17	0.34	0.57	0.87
	3000 won	0	0.01	0.08	0.20	0.39	0.65	0.99
Model C0	0 won	0	0	0	0	0	0	0
	500 won	0	0.00	0.00	0.01	0.02	0.05	0.09
	1000 won	0	0.00	0.01	0.03	0.06	0.12	0.19
	1500 won	0	0.00	0.02	0.05	0.11	0.19	0.30
	2000 won	0	0.00	0.02	0.07	0.14	0.25	0.39
	2500 won	0	0.00	0.02	0.07	0.16	0.29	0.46
	3000 won	0	0.00	0.02	0.08	0.17	0.31	0.50
Model B0	0 won	0	0	0	0	0	0	0
	500 won	0	0.00	0.02	0.04	0.07	0.11	0.16
	1000 won	0	0.00	0.03	0.08	0.14	0.22	0.31
	1500 won	0	0.00	0.04	0.10	0.20	0.31	0.45
	2000 won	0	0.00	0.04	0.11	0.23	0.38	0.56
	2500 won	0	0.00	0.03	0.11	0.24	0.42	0.63
	3000 won	0	-0.01	0.03	0.11	0.24	0.42	0.65

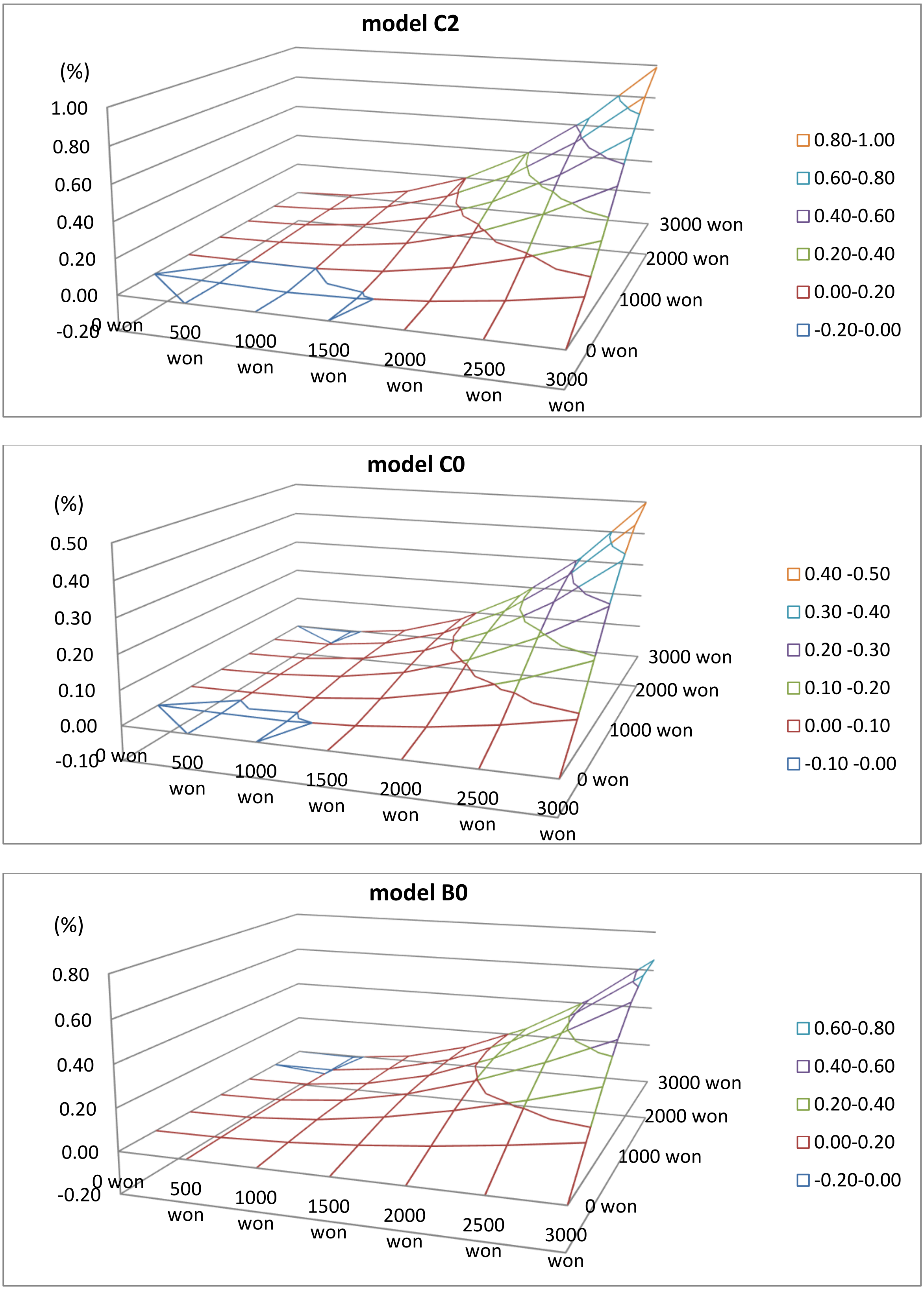
Appendix Figure 6-2. The modal shift synergy effects of PT commuting cost subsidies and additional parking fees in models with no statistically significant coefficient related to interaction effects







Appendix Figure 6-3. The modal shift synergy effects of PT commuting cost subsidies and congestion charges in models with no statistically significant coefficient related to interaction effects



Appendix Table 6-2. The modal shift probability curve of the combined MSPs

	subsidy / parking	0 won	500 won	1000 won	1500 won	2000 won	2500 won	3000 won
PT commuting cost subsidy + additional parking fee								
Model C2	0 won	39.62	42.17	44.76	47.38	50.00	52.61	55.17
	500 won	42.17	44.76	47.38	50.00	52.61	55.17	57.68
	1000 won	44.76	47.38	50.00	52.61	55.17	57.68	60.12
	1500 won	47.38	50.00	52.61	55.17	57.68	60.12	62.47
	2000 won	50.00	52.61	55.17	57.68	60.12	62.47	64.72
	2500 won	52.61	55.17	57.68	60.12	62.47	64.72	66.88
	3000 won	55.17	57.68	60.12	62.47	64.72	66.88	68.92
Model C0	0 won	42.54	44.79	47.06	49.35	51.63	53.89	56.13
	500 won	44.79	47.06	49.35	51.63	53.89	56.13	58.34
	1000 won	47.06	49.35	51.63	53.89	56.13	58.34	60.49
	1500 won	49.35	51.63	53.89	56.13	58.34	60.49	62.59
	2000 won	51.63	53.89	56.13	58.34	60.49	62.59	64.63
	2500 won	53.89	56.13	58.34	60.49	62.59	64.63	66.60
	3000 won	56.13	58.34	60.49	62.59	64.63	66.60	68.49
Model B0	0 won	48.18	50.36	52.53	54.68	56.81	58.91	60.97
	500 won	50.36	52.53	54.68	56.81	58.91	60.97	62.98
	1000 won	52.53	54.68	56.81	58.91	60.97	62.98	64.92
	1500 won	54.68	56.81	58.91	60.97	62.98	64.92	66.81
	2000 won	56.81	58.91	60.97	62.98	64.92	66.81	68.63
	2500 won	58.91	60.97	62.98	64.92	66.81	68.63	70.37
	3000 won	60.97	62.98	64.92	66.81	68.63	70.37	72.05
PT commuting cost subsidy + congestion charges								
	subsidy / congestion	0 won	500 won	1000 won	1500 won	2000 won	2500 won	3000 won
Model C2	0 won	39.62	42.17	44.77	47.38	50.00	52.61	55.17
	500 won	42.17	44.77	47.38	50.00	52.61	55.17	57.68
	1000 won	44.77	47.38	50.00	52.61	55.17	57.68	60.12
	1500 won	47.38	50.00	52.61	55.17	57.68	60.12	62.47
	2000 won	50.00	52.61	55.17	57.68	60.12	62.47	64.73
	2500 won	52.61	55.17	57.68	60.12	62.47	64.73	66.88
	3000 won	55.17	57.68	60.12	62.47	64.73	66.88	68.92
Model C0	0 won	42.54	44.83	47.14	49.46	51.78	54.08	56.35
	500 won	44.83	47.14	49.46	51.78	54.08	56.35	58.58
	1000 won	47.14	49.46	51.78	54.08	56.35	58.58	60.76
	1500 won	49.46	51.78	54.08	56.35	58.58	60.76	62.88
	2000 won	51.78	54.08	56.35	58.58	60.76	62.88	64.94
	2500 won	54.08	56.35	58.58	60.76	62.88	64.94	66.92
	3000 won	56.35	58.58	60.76	62.88	64.94	66.92	68.82
Model B0	0 won	48.18	50.46	52.74	55.00	57.23	59.42	61.56
	500 won	50.46	52.74	55.00	57.23	59.42	61.56	63.64
	1000 won	52.74	55.00	57.23	59.42	61.56	63.64	65.65
	1500 won	55.00	57.23	59.42	61.56	63.64	65.65	67.58
	2000 won	57.23	59.42	61.56	63.64	65.65	67.58	69.44
	2500 won	59.42	61.56	63.64	65.65	67.58	69.44	71.21
	3000 won	61.56	63.64	65.65	67.58	69.44	71.21	72.90

Appendix 7. Detailed Result of the Segmentation Analysis with Socio-demographic Variables

1. Gender

Gender is a representative factor in the segmentation analysis.

(1) The segmentation method using dummy variables

In **Appendix Table 7-1**, rho-squared index (ρ^2) of the segmented model (0.330) is higher than that of the basic model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of MSP with a segmented model are the same as those of the default model B0.

Appendix Table 7-1. The coefficients of a segmented model with a dummy variable (Gender)

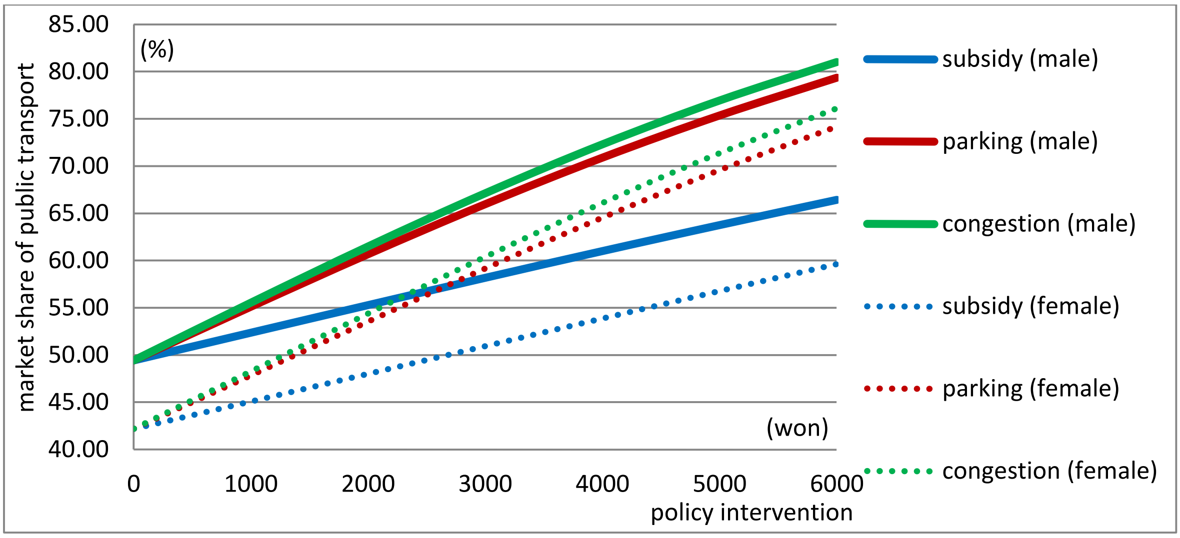
Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	0.0233	0.5876
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1175**	**12.8150****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2284**	**-23.3305****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2455**	**-29.3807****
Dummy gender (male:0, female:1)	β_{gender}			**0.2915**	**-5.4757****
L(0)		-12405.26		-12405.26	
$L(\widehat{\beta})$		-8389.1		-8306.915	
ρ^2		0.324		0.330	
Number of observations		678		672	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

If a respondent is female, the value of the dummy attribute will be one. Conversely, if a respondent is male, the value of the dummy attribute will be zero. Thus, if a respondent is female, the value of the coefficient (0.2915) is multiplied by the value of the attribute (1) (= 0.2915×1). Therefore, the utility value of the dummy variable (female) will be 0.2915. In addition, since the sign of the dummy variable (0.2915) is positive, it is expected that the females tend to prefer the use of a car. However, this result is different from the common idea. This may be that the females tend to use PT more than the males. Since the main purpose of this research is modal shift evaluation from car to PT, the participation of this survey focuses on car users. As a result, it can be inferred that since many women, who usually use PT as a travel mode and think of their participation useless, cannot contribute to survey, or even may interrupt the survey, they did not participate in the survey. That is, it can be inferred that in terms of the research purpose, the females who are usually used to using PT were prone to abandon the participation of this survey. What is more, considering the ratio of female workers in the Gangnam area (39%), the lower survey participation ratio of females (15%) can be explained with the same reasons. The phenomenon may be due to a more pragmatic tendency of the females compared to the males. Accordingly, this result should be merely interpreted as the participation of women who are used to using a car is relatively higher than that of men.

Appendix Figure 7-1 shows the market share of PT with regard to gender factor in the segmented model using a dummy variable. The position of the intercept of the females on the vertical axis is lower than that of the males. It suggests that the females prefer the use of a car rather than the males.

Appendix Figure 7-1. The market share of PT in the segmented model using a dummy variable (Gender)



(2) The segmentation method using separate data of the segmented groups

In **Appendix Table 7-2**, the absolute value of the coefficient β_1 of the males (0.1024) is indisputably lower than that of the coefficient β_2 (0.2119). It would seem to indicate that the modal shift effect of PT commuting cost subsidies for the male is lower than that of the females.

Although possible causes are reviewed to find out the reason for the major differences, no obvious cause can be found. That is, the difference between the females (mean: 2,005.00 won, = £1.11) and the males (mean: 1,985.22 won,= £1.10) in terms of the total PT commuting cost is insignificant. Also, the discrepancy between the females and the males about individual attitudes toward cost (five-point Likert scales of question about 'cost is a very important factor in determining commuting.' → 1: strongly disagree ~ 5: strongly agree) is small[15]. From the result of individuals' attitudes about congestion severity (five-point Likert scales of question about 'congestion problems are very severe

[15] Frequency distribution of individual attitude to importance of cost

Gender	1 scale	2 scale	3 scale	4 scale	5 scale	Missing data	Sum
Male	3 (0.46%)	29 (4.48%)	153 (23.65%)	299 (46.21%)	155 (23.96%)	8 (1.24%)	647 (100%)
Female	0	6 (5.31%)	26 (23.01%)	52 (46.12%)	26 (23.01%)	3 (2.65%)	113 (100%)

during the morning peak.' → 1: strongly disagree ~ 5: strongly agree), there is no significant difference between the males and the females[16]. However, the awareness of the congestion severity does not seem to affect the weak modal shift effect of the PT commuting cost subsidies for the males significantly. Consequently, it can be inferred that an intrinsic gender factor influences the weak modal shift effects of the PT commuting cost subsidies for the males.

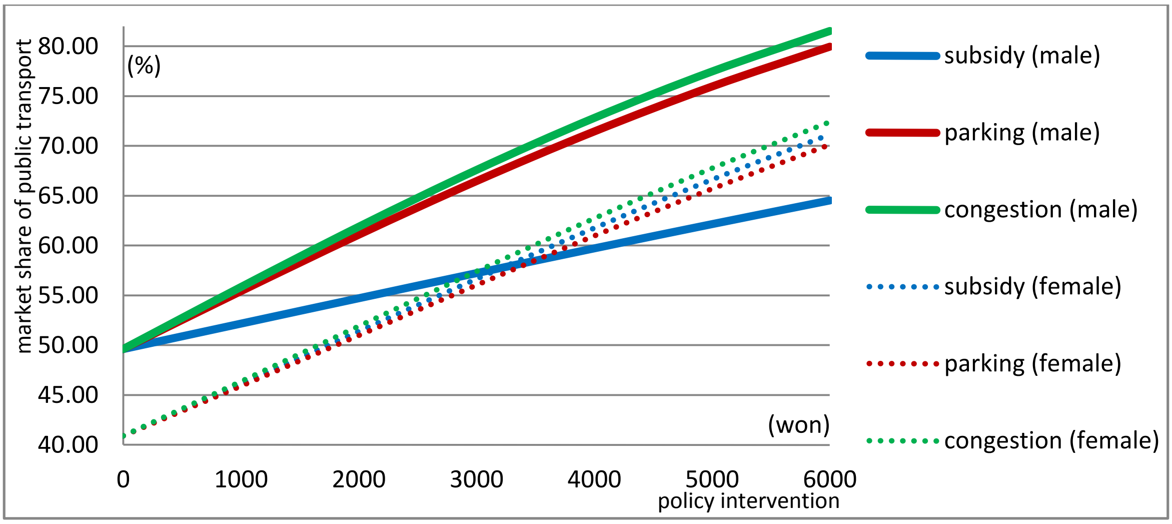
Appendix Table 7-2. The coefficients of segmented models using separate data (Gender)

Coefficient		Male		Female	
		Beta	t-value	Beta	t-value
ASC	β_0	0.0157	0.3728	**0.3677**	**3.6224****
PT commuting cost subsidy	β_1	0.1024	**10.5131****	0.2119	**8.0656****
Additional parking fee	β_2	**-0.2334**	**-21.8291****	**-0.2036**	**-8.3099****
Congestion charge	β_3	**-0.2503**	**-27.3949****	**-0.2222**	**-10.6924****
L(0)		-10582.97		-1714.846	
$L(\widehat{\beta})$		-7030.207		-1266.752	
ρ^2		0.33571		0.26130	
Number of observations		647		113	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

As shown in **Appendix Figure 7-2**, the position of the intercept of females on the vertical axis is lower than that of the males. In addition, the slope of the graph related to the PT commuting cost subsidies for the males is obviously lower than the other graph. This graph coincides with the coefficient β_1 of the males in **Appendix Table 7-2**. More specifically, the modal shift effects of the PT commuting cost subsidies for the females are stronger than those of the additional parking fee.

Appendix Figure 7-2. The market share of PT in the segmented model using separate data (Gender)



[16] Frequency distribution of individual attitude to congestion severity

Gender	1 scale	2 scale	3 scale	4 scale	5 scale	Missing data	Sum
Male	5 (0.77%)	10 (1.55%)	51 (7.88%)	226 (34.93%)	353 (54.56%)	2 (0.31%)	647 (100%)
Female	0	3 (2.65%)	5 (4.42%)	43 (38.05%)	61 (53.98%)	1 (0.88%)	113 (100%)

2. Age

Age can be a main segmentation factor. Age can be classified into three categories: the 20-30s, the 40s, and the 50s or more.

(1) The segmentation method using dummy variables

In **Appendix Table 7-3**, the ρ^2 of the segmented model (0.350) is higher than that of the default model (0.324). Moreover, the signs and the orders of the magnitude of the coefficients of the MSP with a segmented model are the same as those of the default model (model B0).

The sign of the coefficient of the ASC (β_0) is negative. The negative ASC means that individuals prefer the use of PT as a travel mode if all the five variables are the same (Takama and Preston, 2008). This is mainly because the ASC (β_0: – 0.4285) is attributable to the utility function of the car in the model specification. Considering the positive sign of the ASC in the default model (model B0), it can be inferred that the inclusion of the age dummy variables in the specification of the segmented model causes the increase of PT use. That is, since the default value is not included in the other age dummy variables, it can be interpreted that the reflection of the default value affects the value of the ASC in the specification of the utility function. In this case, the age group composed of respondents in their 20s and 30s (low-age group) is set up as the default value. Meanwhile, the coefficient of the ASC (β_0) is statistically significant at the 1% level of confidence since the absolute t-value (– 9.0355) is greater than 2.57.

If a respondent is in his/her 40s (middle-age group), the value of the dummy attribute (Dummy age 1) will be one. In this case, the value of the coefficient (0.7779) is multiplied by the value of the attribute (1) (= 0.7779×1). Thus, the utility value of the dummy variable (middle-age group) will be 0.7779. In addition, if a respondent is in their 50s or more (high-age group), the value of the dummy attribute (Dummy age 2) will be one. In this case, the value of the coefficient (0.9329) is multiplied by the value of the attribute (1) (= 0.9329×1). The utility value of the dummy variable (high-age group) will be 0.9329. Meanwhile, if a respondent is in their 20s and 30s (low-age group), the value of the dummy attribute will be zero. This is because the default value of the dummy attribute is set up as the low-age group. The value (0.9329) of the coefficient for the dummy variable of the high-age group is larger than that (0.7779) of the middle-age group. In addition, since the signs of the dummy variables are positive, the two dummy variables will contribute to the increase of the utility of the car. In conclusion, because the magnitude of the coefficient of the elderly is larger than that of the younger, it can be interpreted that the elderly tend to prefer the use of a car.

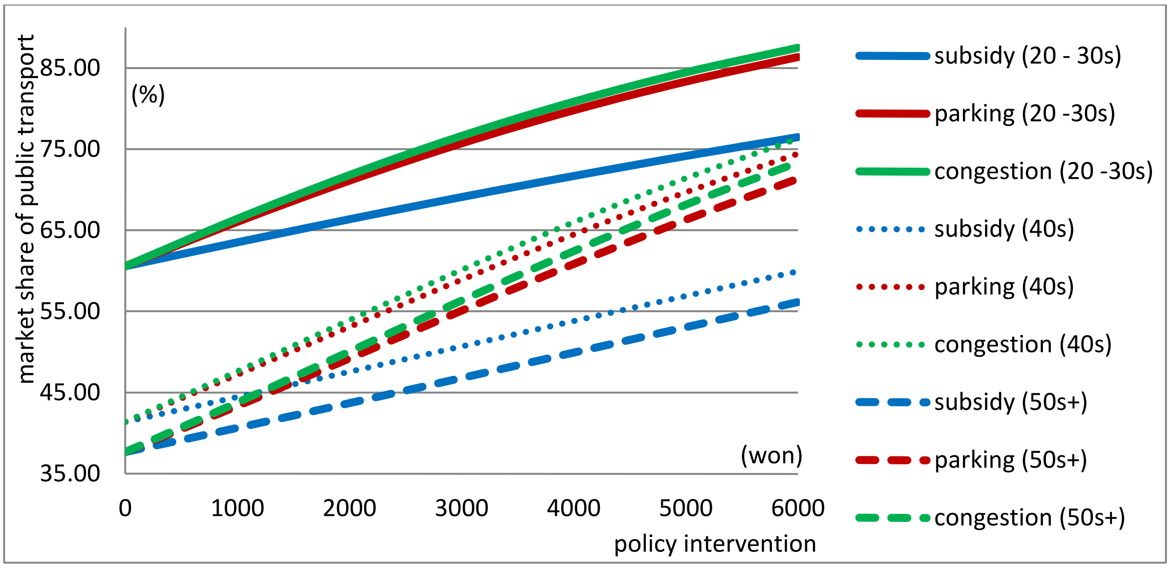
Appendix Table 7-3. The coefficients of a segmented model with dummy variables (Age)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**-0.4285**	**-9.0355****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1252**	**13.4800****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2362**	**-23.6961****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2530**	**-29.7230****
Dummy age 1 (20-30s:0, 40s:1)	β_{age1}			**0.7779**	**17.2045****
Dummy age 2 (20-30s:0, 50s+:1)	β_{age2}			**0.9329**	**16.1673****
L(0)		-12405.26		-12405.26	
$L(\widehat{\beta})$		-8389.1		-8064.78	
ρ^2		0.324		0.350	
Number of observations		678		671	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

As can be seen in **Appendix Figure 7-3**, the elderly tend to prefer car use while the younger are more likely to prefer the use of PT. This result is acceptable and sensible. In addition, the interval between the low-age group and the middle-age group is wider than the one between the middle-age group and the high-age group. This result is also acceptable and sensible regarding the economic power gap in terms of generation.

Appendix Figure 7-3. The market share of PT in the segmented model using dummy variables (Age)



(2) The segmentation method using separate data of the segmented groups

The sign of ASC for the low-age group is negative. It indicates that the low-age group prefers the use of PT rather than the use of a car. As shown in **Appendix Table 7-4**, the marginal utility (β_1) of the PT commute cost subsidies for the low-age group (0.2278) is greater than that of the middle-age group (0.1717) and the high-age group (– 0.0060). It appears that the modal shift effect of the PT commuting cost subsidies for the low-age group is higher than that of other groups. In addition, as for the low-age group, the value of the coefficient for additional parking fees (– 0.2589) is higher than congestion charges (– 0.2506). This is an exceptional case that deviates from the general trends.

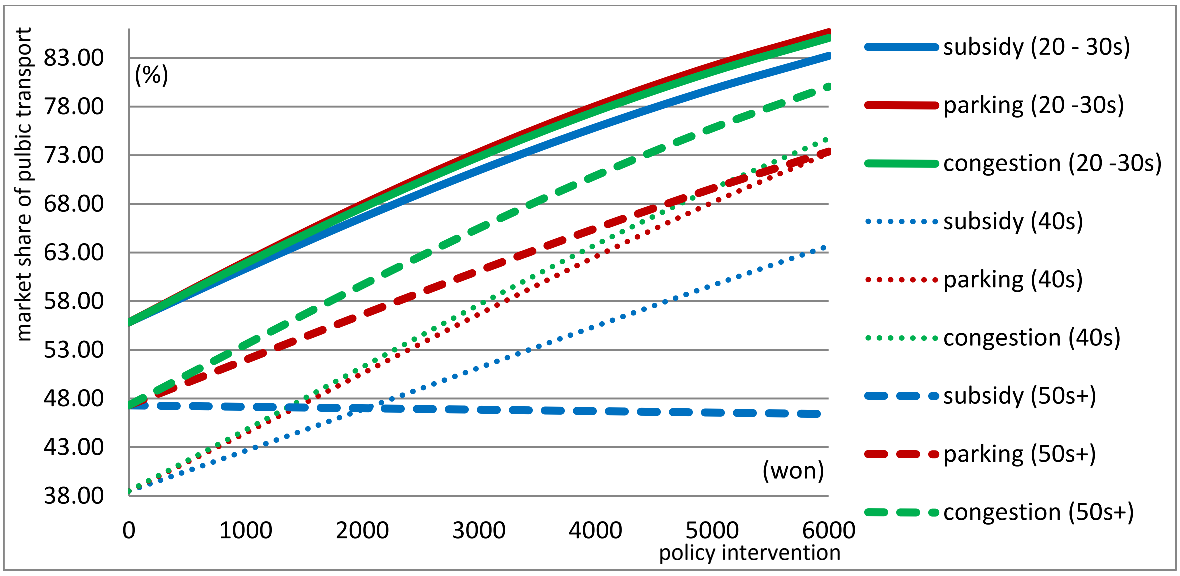
Appendix Table 7-4. The coefficients of segmented models using separate data (Age)

Classification		20-30s (low age group)		40s (middle age group)		50s+ (high age group)	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**-0.2330**	**-3.3789****	**0.4686**	**8.0961****	0.1081	1.2474
PT commute cost subsidy	β_1	**0.2278**	**10.7281****	**0.1717**	**12.7101****	-0.0060	-0.5119
Additional parking fee	β_2	**-0.2589**	**-13.9825****	**-0.2455**	**-17.3962****	**-0.1869**	**-8.4230****
Congestion charge	β_3	**-0.2506**	**-15.9056****	**-0.2587**	**-21.5327****	**-0.2494**	**-13.1011****
L(0)		-4874.904		-5466.852		-1938.04	
$L(\widehat{\beta})$		-2568.455		-3921.76		-1510.91	
ρ^2		0.47313		0.28263		0.22039	
Number of observations		283		346		130	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Most coefficients (β_1, β_2 and β_3) are statistically significant at the 99% confidence interval since the absolute t-values are larger than 2.57. However, the coefficient β_1 of the high-age group is statistically insignificant since the absolute t-values (– 0.5119) are less than 1.65. Furthermore, the sign of the coefficient β_1 (– 0.0060) is negative. Since the implementation of the PT commute cost subsidies usually encourages the use of PT, the sign of the coefficient β_1 should be positive in the utility function of PT use. Therefore, the negative sign must be an inverse sign. As a result, this coefficient should be excluded in the interpretation of the coefficient.

Appendix Figure 7-4. The market share of PT in the segmented models using separate data (Age)



In **Appendix Figure 7-4**, it seems to be that the high-age group is prone to prefer the use of PT rather than the middle-age group. However, this result is different from the general trend. The general trend is that the younger seem to prefer the use of PT. That is, although **Appendix Figure 7-3** shows the acceptable findings, **Appendix Figure 7-4** shows the contrary. As a result, in terms of the judgement of the position of the intercept, a segmented model using dummy variables is better than segmented models using separated data of segmented groups. This result seems to indicate a drawback in the segmentation model using separate data of segmented groups.

3. Education career

Education can be a main segmentation factor. This factor can also be classified into three categories: below the university group (low-education group), the undergraduate group (middle-education group), and the postgraduate group (high-education group). In general, the highly educated might behave differently to the less educated.

(1) The segmentation method using dummy variables

In **Appendix Table 7-5**, the ρ^2 of the segmented model (0.330) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients for the MSP with a segmented model are the same as those of the default model B0.

The sign of the coefficient of the ASC (0.2591) is negative. The negative ASC means that individuals prefer the use of PT in the interpretation of the utility function. Considering the positive sign of the ASC in the default model, it can be inferred that the inclusion of the educational dummy variables and the reflection of default value (low-education group) in the specification of the segmented model cause the increase of PT use. The coefficient of the ASC (β_0) is statistically significant at the 1% level of confidence since the absolute t-value (– 2.9021) is greater than 2.57.

If a respondent belongs to the middle-education group, the value of the dummy attribute (Dummy education 1) will be one. In this case, the value of the coefficient (0.2706) is multiplied by the value of the attribute (1) (= 0.2706×1). The utility value of the dummy variable (middle-education group) will be 0.2706. In addition, if a respondent is in the high-education group, the value of the dummy attribute (Dummy education 2) will be 1. In this case, the value of the coefficient (0.5176) is multiplied by the value of the attribute (1) (= 0.5176×1). The utility value of the dummy variable (high-education group) will be 0.5176. Meanwhile, if a respondent is attached to the low-education group, the value of the dummy attribute will be zero. As can be seen in **Appendix Table 7-5**, the value (0.5176) of the coefficient of the dummy variable for the high-education group is larger than that (0.2706) of the middle-education group. Therefore, it can be inferred that the high-education group are more likely to prefer the use of a car. In addition, since the signs of the dummy variables are positive, the dummy variables will contribute to the increase of the utility of the car. In conclusion, since the magnitude of the coefficient of the high-education group is larger than the low-education group, it is interpreted that the highly educated people tend to prefer the use of a car.

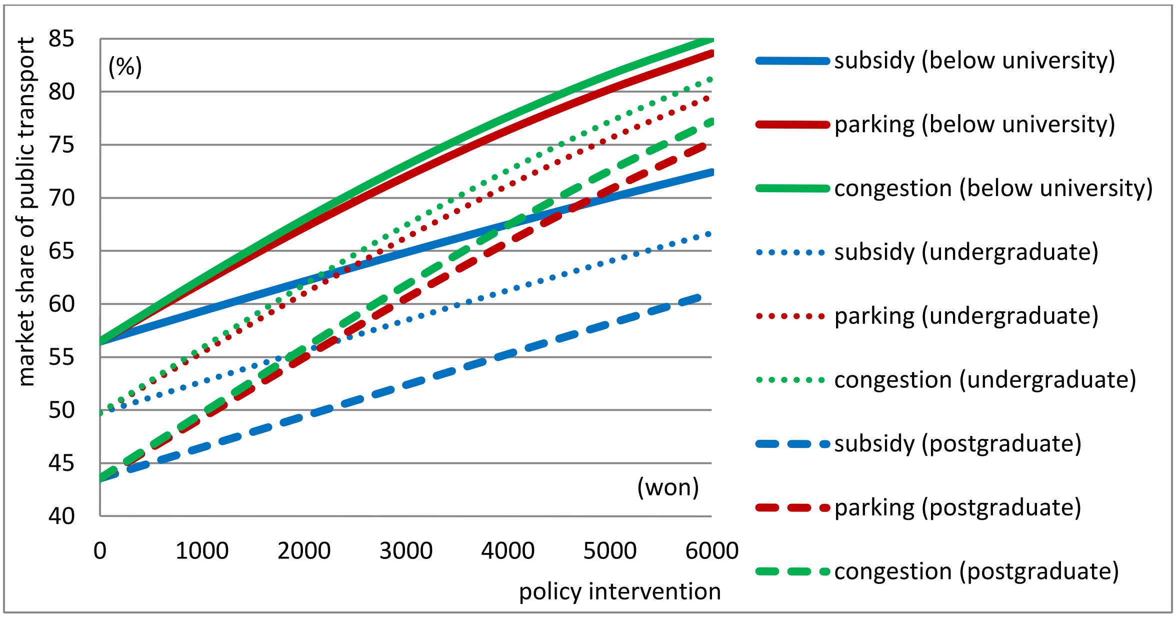
Appendix Table 7-5. The coefficients of a segmented model with dummy variables (Education)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**-0.2591**	**-2.9021****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1176**	**12.8700****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2285**	**-23.3457****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2462**	**-29.4713****
Dummy education 1 (low edu:0, middle edu:1)	$\beta_{edu\,1}$			**0.2706**	**3.1148****
Dummy education 2 (low edu:0, high edu:1)	$\beta_{edu\,2}$			**0.5176**	**5.7376****
L(0)		-12405.26		-12405.26	
$L(\widehat{\beta})$		-8389.1		-8312.738	
ρ^2		0.324		0.330	
Number of observations		678		673	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

As indicated in **Appendix Figure 7-5**, the low-education group tend to use PT more than the high-education ones. This result is acceptable and logical in terms of common sense.

Appendix Figure 7-5. The market share of PT in the segmented model using dummy variables (Education)



(2) The segmentation method using separate data of the segmented groups

In **Appendix Table 7-6**, the value of the coefficient β_1 of the high-education group (0.1735) is greater than that of the low-education group (0.1427) and the middle-education group (0.0926). It indicates that the modal shift effects of the PT commuting cost subsidies for the high-education group are higher than those of the other groups. In terms of the modal shift effects of the PT commuting cost subsidies, the lowest group is the middle-education group.

Appendix Table 7-6. The coefficients of segmented models using separate data (Education)

Classification		Below University		Undergraduate		Postgraduate	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**-0.3785**	**-2.3114***	-0.0496	-1.0298	**0.4242**	**5.8941****
PT commuting cost subsidy	β_1	**0.1427**	**3.2443****	**0.0926**	**8.5338****	**0.1735**	**9.7997****
Additional parking fee	β_2	**-0.1833**	**-4.4025****	**-0.2259**	**-18.3733****	**-0.2427**	**-13.7977****
Congestion charge	β_3	**-0.2114**	**-5.9411****	**-0.2421**	**-23.0405****	**-0.2616**	**-17.4650****
L(0)		-775.6317		-7971.193		-3569.015	
$L(\widehat{\beta})$		-472.0411		-5297.165		-2533.955	
ρ^2		0.39141		0.33546		0.29001	
Number of observations		47		493		222	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Appendix Table 7-7 shows the distribution of the income group classified by education. Overall, the level of the education group would seem to correspond to the class of the income group. However, the income distribution factor does not seem to affect the weak modal shift effect of the PT commuting cost subsidies for the middle-education group significantly.

Appendix Table 7-7. Distribution of income class classified by education

Classification	Less educated Group	Middle educated Group	Highly educated Group	Total
Low income	30 (63.83%)	238 (48.37%)	75 (33.78%)	343 (45.07%)
Middle income	10(21.28%)	146 (29.67%)	68 (30.63%)	224 (29.43%)
High income	7 (14.89%)	108 (21.95%)	79 (35.59%)	194 (25.49%)
Total	47 (6.18%)	492 (64.65%)	222 (29.17%)	761 (100%)

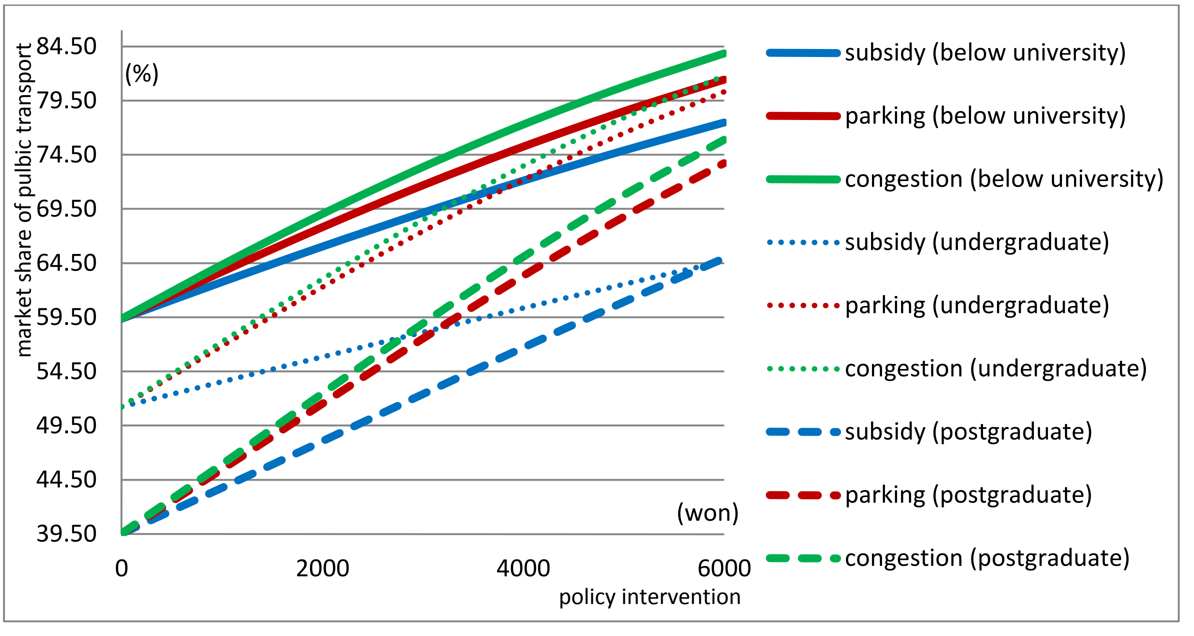
In addition, the discrepancy of individual ecological awareness of the environment (five-point Likert scales of question about 'the use of PT is important in order to reduce global warming and to protect the environment.' 1: strongly disagree ~ 5: strongly agree) according to the education group is reviewed. However, the environmental awareness does not appear to show any significant differences according to the income groups. **Appendix Table 7-8** illustrates the distribution of the environmental awareness according to the educational group. However, the conscious environmental factor does not seem to affect the weak modal shift effects of the PT commuting cost subsidies significantly. Therefore, if can be inferred that there are intrinsic educational group factors of influencing the weak modal shift effect of the PT commuting cost subsidies.

Appendix Table 7-8. Distribution of environment awareness classified by educational career

Classification	Less educated group	Middle educated Group	Highly educated group	Total
Low environmental awareness	20 (42.55%)	188 (38.84%)	77 (35%)	285 (37.95%)
Middle environmental awareness	21 (**44.68**%)	220 (**45.45**%)	110 (**50**%)	351 (46.74%)
High environmental awareness	6 (12.77%)	77 (15.70%)	33 (15%)	115 (15.31%)
Total	47 (6.26%)	484 (64.45%)	220 (29.29%)	751 (100%)

In **Appendix Figure 7-6**, the modal shift effects of the PT commuting cost subsidies for the middle-education group appear to show the lowest effectiveness. It implies that the middle-education group is less sensitive to the PT commute cost subsidies than other groups.

Appendix Figure 7-6. The market share of PT in the segmented models using separate data (Education)



4. Occupation career

Occupation can be a main segmentation factor. In addition, considering the size of the survey samples in this research, the occupation can be classified into two categories: the administrative or clerical sector and the other sectors. In general, people who work in the administrative or clerical sector might behave differently to people who work in other sectors such as the governmental sector, specialized sector, technical sector, sales sector, service sector, production, drive or labour sector, and so on.

(1) The segmentation method using a dummy variable

In **Appendix Table 7-9**, the ρ^2 of the segmented model (0.335) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with a segmented model are the same as a default model B0. The sign of the coefficient of the ASC (β_0) is positive. The positive ASC suggests that individuals prefer the use of a car in the interpretation of the utility function.

If a respondent works in the administrative or clerical sector, the value of the dummy attribute will be one. Conversely, if a respondent works in other sectors, the value of the dummy attribute will be zero. Thus, if a respondent works in the administrative or clerical sector, the value of the coefficient (– 0.5510) is multiplied by the value of the attribute (= – 0.5510×1). The utility value of the dummy variable will be – 0.5510. The negative sign of the coefficient of the dummy variable (– 0.5510) indicates that people who belong to the dummy variable group tend to prefer the use of PT. In this case, commuters who work in the administrative or clerical sector tend to prefer the use of PT as opposed to people who work in other sector.

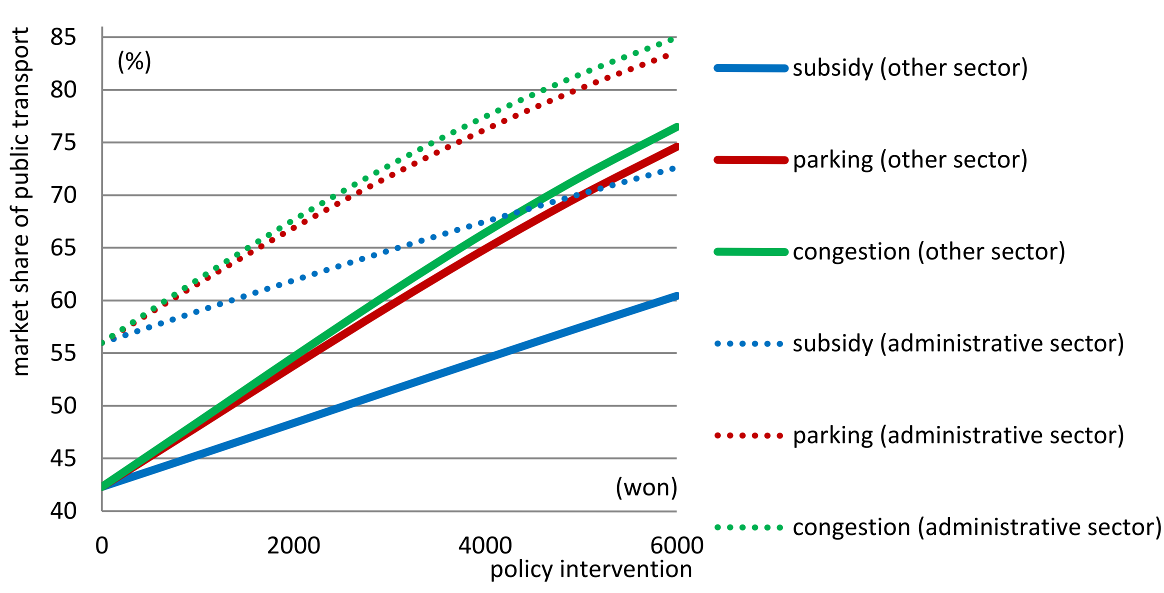
Appendix Table 7-9. The coefficients of a segmented model with a dummy variable (Occupation)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**0.3105**	**7.2703****
PT Commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1224**	**13.3478****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2311**	**-23.5121****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2483**	**-29.6025****
Dummy occupation (other sectors:0, administrative or clerical sector:1)	β_{work}			**-0.5510**	**-13.6528****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8254.974	
ρ^2		0.324		0.335	
Number of observations		678		674	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Figure 7-7**, the position of the intercept of commuters who work in the administrative or clerical sector is higher than that of workers in other sectors. It points to the fact that people who work in the administrative or clerical sector tend to prefer the use of PT rather than people who work in other sectors.

Appendix Figure 7-7. The market share of PT in the segmented model using a dummy variable (Occupation)



(2) The segmentation method using separate data of the segmented groups

Appendix Table 7-10. The coefficients of segmented models using separate data (Occupation)

Coefficient		Other sectors		Administrative sector	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.1956**	**3.9558****	-0.0214	-0.3374
PT Commuting cost subsidy	β_1	**0.0896**	**8.5223****	**0.2044**	**11.2691****
Additional parking fee	β_2	**-0.2128**	**-17.4705****	**-0.2652**	**-15.8734****
Congestion charge	β_3	**-0.2430**	**-23.3638****	**-0.2582**	**-18.1868****
L(0)		-7036.83		-5297.031	
$L(\widehat{\beta})$		-5171.454		-3065.016	
ρ^2		0.26509		0.42137	
Number of observations		444		319	

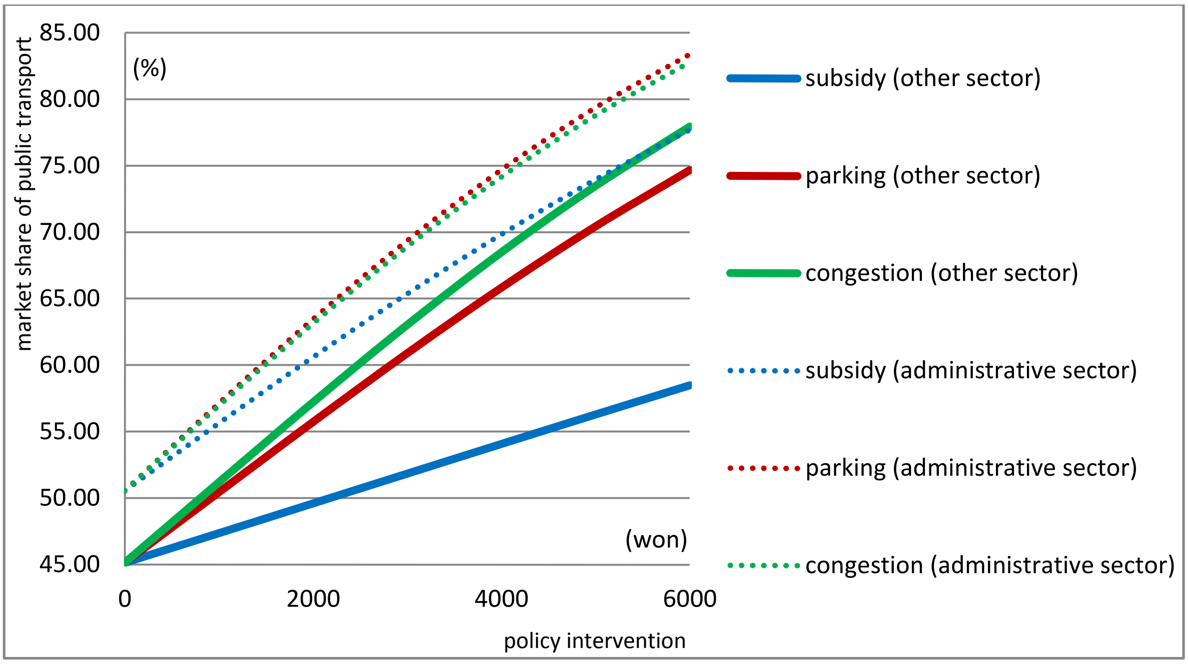
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Appendix Table 7-10 shows the coefficients of segmented models using separate data of the segmented groups. All the coefficients (β_1, β_2 and β_3) related to the MSP for commuters who work in the administrative or clerical sector are higher than those of commuters who work in other sectors.

That is to say, the modal shift effects of MSP for workers in the administrative or clerical sector are higher than those of workers in other sectors.

The absolute value of the coefficient β_1 of workers in other sector (0.0896) is much lower than that of workers in the administrative or clerical sectors (0.2044). This implies that the modal shift effects of the PT commuting cost subsidies for workers in other sectors is weaker than workers in the administrative or clerical sectors. Interestingly, for commuters who work in the administrative or clerical sectors, the value of the coefficient of additional parking fees (– 0.2652) is higher than that of congestion charges (– 0.2582). This is an exceptional case that deviates from the general trends.

Appendix Figure 7-8. The market share of PT in the segmented models using separate data (Occupation)



In **Appendix Figure 7-8**, people who work in the administrative or clerical sector are prone to prefer the use of PT rather than people who work in the other sectors. In addition, the modal shift effects of additional parking fees of people who work in the administrative or clerical sector are stronger than those of congestion charges. This result would appear to correspond to the coefficients β_2 and β_3 in **Appendix Table 7-10**.

5. Income

Income can be a main segmentation factor. The income factor can be classified into three categories: low, middle, and high-income group. In this case, total household income data from all sources before tax per month from the survey are used.

(1) The segmentation method using dummy variables

In **Appendix Table 7-11**, the ρ^2 of the segmented model (0.341) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with a segmented model are the same as those of the default model.

The sign of the coefficient of the ASC (β_0) of the segmented model is negative. The negative ASC means that individuals seem to prefer the use of PT. Considering the positive sign of the ASC in the default model (model B0), it can be inferred that the inclusion of the income dummy variables in the specification of the segmented model causes the increase of PT use. In other words, since the default value is not included in the other income dummy variables, it can be interpreted that the reflection of the default value (low-income group) affects the value of the ASC in the specification of the utility functions. The income group that is composed of a respondent whose household income is less than 5,000,000 won per month (low-income group) is set up as the default value.

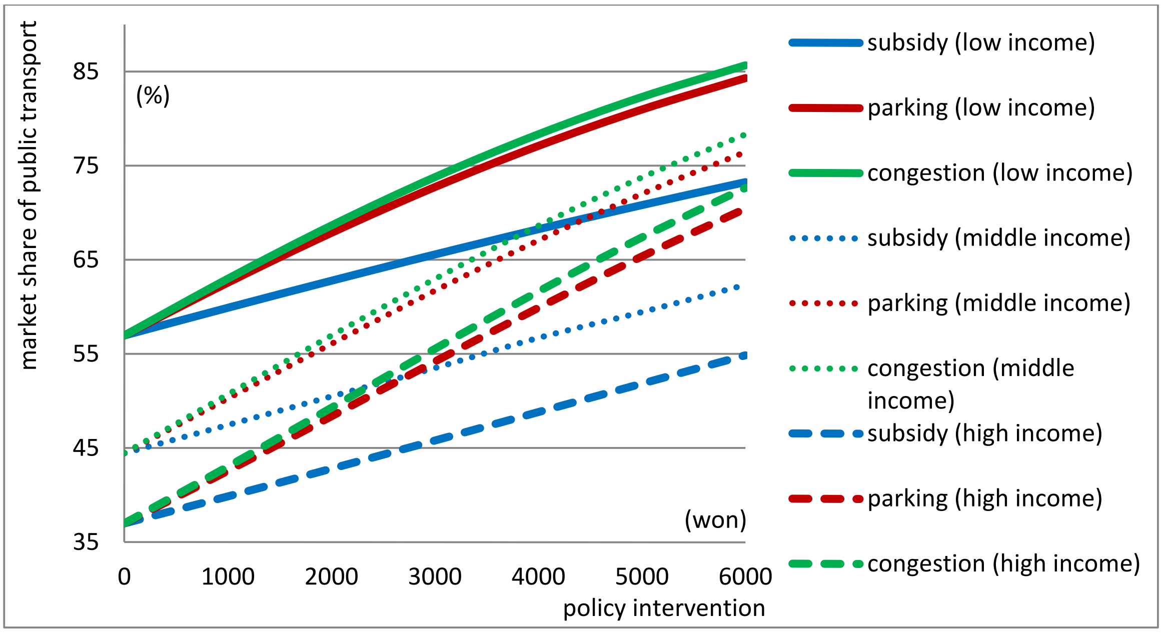
Appendix Table 7-11. Coefficients of a segmented model with dummy variables (Income)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**-0.2808**	**-6.2210****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1211**	**13.0113****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2334**	**-23.5898****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2514**	**-29.7452****
Dummy income 1 (low income:0, **middle income:1**)	$\beta_{income\ 1}$			**0.5035**	**10.7775****
Dummy income 2 (low income:0, **high income:1**)	$\beta_{income\ 2}$			**0.8126**	**16.9600****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8171.184	
ρ^2		0.324		0.341	
Number of observations		678		675	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

If a respondent's household income is between 5,000,000 won and 7,000,000 won per month (middle-income group), the value of the dummy attribute (Dummy income 1) will be one. In this case, the value of the coefficient (0.5035) is multiplied by the value of the attribute (1) (= 0.5035×1). These utility values of the dummy variable (middle-income group) will be 0.5035. In addition, if a respondent's household income is more than 7,000,000 won (high-income group), the value of the dummy attribute (Dummy income 2) will be one. In this case, the value of the coefficient (0.8126) is multiplied by the value of the attribute (1) (= 0.8126×1). This utility value of the dummy variable (high-income group) will be 0.8126. At the same time, if a respondent's household income is less than 5,000,000 won per month (low-income group), the value of the dummy attribute (default value) will be zero. In addition, since the signs of the dummy variables are positive, the dummy variables will contribute to an increase in the utility of car use. Therefore, since the magnitude of the coefficient of the rich is larger than the poor, it is expected that the rich tend to prefer the use of a car.

Appendix Figure 7-9. The market share of PT in the segmented model using dummy variables (Income)



As can be seen in **Appendix Figure 7-9**, the rich tend to prefer the car usage more than the poor. This result is sensible and logical.

(2) The segmentation method using separate data of the segmented income groups

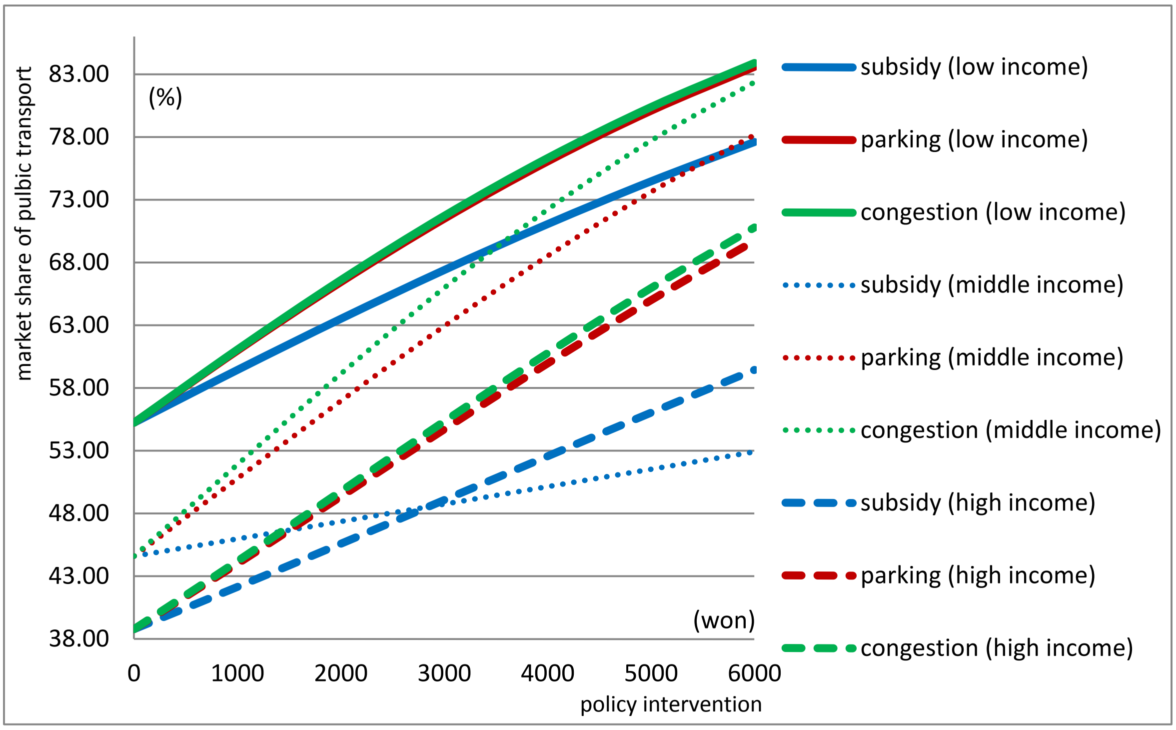
Appendix Table 7-12. The coefficients of segmented models using separate data (Income)

Classification		Low (Up to 5,000t won)		Middle (5,000t ~ 7,000t won)		High (more than 7,000t won)	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**-0.2100**	**-3.43678****	**0.2178**	**3.1420****	**0.4572**	**6.0776****
PT cost subsidy	β_1	**0.1719**	**10.7637****	0.0556	**3.9322****	**0.1399**	**7.8779****
Additional parking fee	β_2	**-0.2364**	**-14.7651****	**-0.2488**	**-14.0260****	**-0.2152**	**-11.9864****
Congestion charge	β_3	**-0.2400**	**-17.5728****	**-0.2932**	**-19.1048****	**-0.2236**	**-14.7539****
L(0)		5771.143		3636.25		2945.182	
L($\widehat{\beta}$)		3304.137		2521.688		2322.89	
ρ^2		0.42747		0.30651		0.21129	
Number of observations		343		225		196	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 7-12**, the value of the coefficient β_1 (0.1719) for the low-income group is greater than those of the middle-income group (0.0556) and the high-income group (0.1399). It means that the modal shift effects of the PT commuting cost subsidies for the low-income group are higher than the other income groups. An interesting point is that the high-income group are more sensitive to the PT commuting cost subsidies rather than the middle-income group. That is, the value of the coefficient β_1 of the middle-income group (0.0556) is much lower than the high-income group (0.1399) or the low-income group (0.1719).

Appendix Figure 7-10. The market share of PT in the segmented models using separate data (Income)



As can be seen in **Appendix Figure 7-10**, the modal shift effects of the PT commuting cost subsidies for the middle-income group are much lower than the high-income group or the low-income group. Due to the low modal shift effect of the middle-income group, it can be more difficult to introduce the overall PT commuting cost subsidy policy. Accordingly, the high-income group usually has a higher market share of the car while the low-income group has a higher market share of PT. Therefore, in real life, it is expected that the middle-income group would be mainly influenced by the MSP as a main target group of the transport policy. However, the result of this research indicates that for the middle-income group, the effectiveness of the PT commuting cost subsidies is very low. In terms of the effectiveness of the modal shift, the expectation is that it is not easy to obtain political acceptability from the general public for the PT commuting cost subsidies.

6. Information based on whether a commuter has a child or children who commute to schools, nurseries or infant caring facilities

Segmentation about whether a commuter has a child or children who commute to schools, nurseries or infant caring facilities could be made since this factor can affect the effect of modal shift on MSP significantly. In general, people who have a child or children might behave differently from people who do not have a child or children. Therefore, whether a commuter has a child or children can be a main segmentation factor.

(1) The segmentation method using a dummy variable

In **Appendix Table 7-13**, the ρ^2 of the segmented model (0.328) is higher than that of the default model B0 (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with a segmented model are the same as those of the default model.

Appendix Table 7-13. Coefficients of a segmented model of using a dummy variable (Child)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	0.3340	6.6690**	0.0449	1.0437
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1165**	**12.7492****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2281**	**-23.3540****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2459**	**-29.5024****
Dummy child (no child: 0, having a child:1)	β_{child}			0.0534	1.3828
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8338.724	
ρ^2		0.324		**0.328**	
Number of observations		678		672	

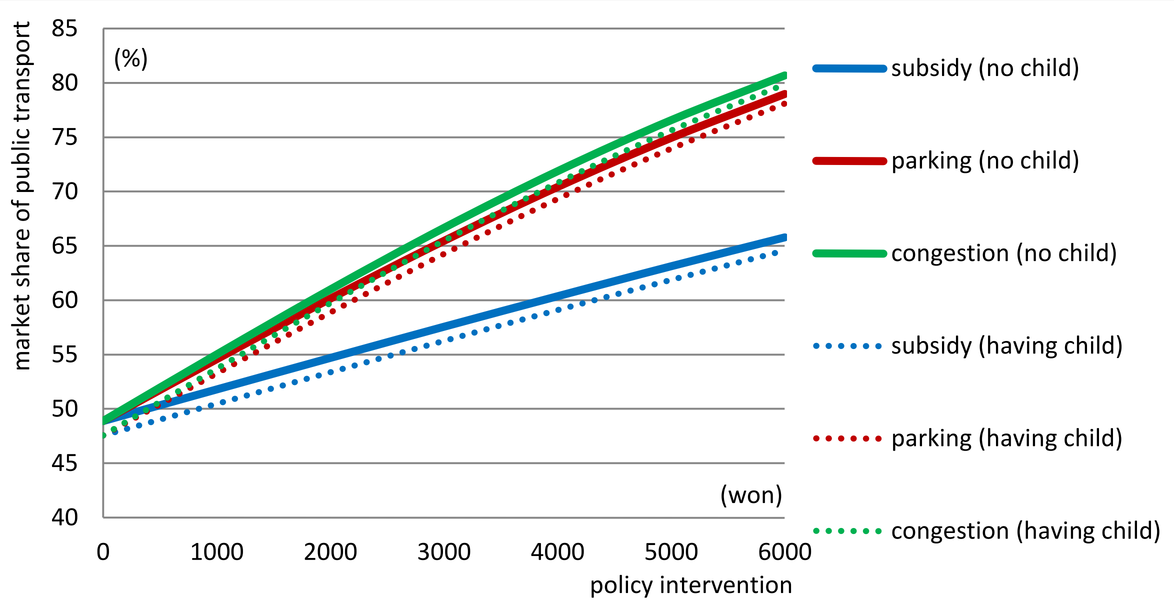
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

If a respondent has a child or children (child group), the value of the dummy attribute will be one. Conversely, if a respondent does not have a child or children (no-child group), the value of the dummy attribute will be zero. Thus, if a respondent has a child or children, the value of the coefficient (0.0534) is multiplied by the value of the attribute (= 0.0534×1). Thus, the utility value of the dummy variable (child group) will be 0.0534. The positive sign of the coefficient of the dummy variable (0.0534) indicates that the child group tends to prefer the use of a car rather than the no-child group.

However, the coefficient of the child dummy variable (β_{child}) is statistically insignificant since the absolute t-value (1.3828) is less than 1.65. Therefore, in terms of statistics, the factor of whether a commuter has a child or children cannot be an appropriate dummy variable. Consequently, in terms of statistics, this segmented factor cannot provide valid differences in each segment.

Appendix Figure 7-11 shows the modal shift effects of the dummy variable about 'whether a commuter has a child or children'. That is, the child group tends to use the car rather than the no-child group. This result is predictable and logical. However, in terms of statistics, meaningful interpretation cannot be applied.

Appendix Figure 7-11. The market share of PT in the segmented model using a dummy variable (Child)



(2) The segmentation method using separate data of the segmented groups

In **Appendix Table 7-14**, the value of the coefficient β_1 (0.1736) of the no-child group is greater than that of the child group (0.1019). Therefore, in terms of the modal shift effect, the effectiveness of the PT commuting cost subsidies for the no-child group is greater than the child group.

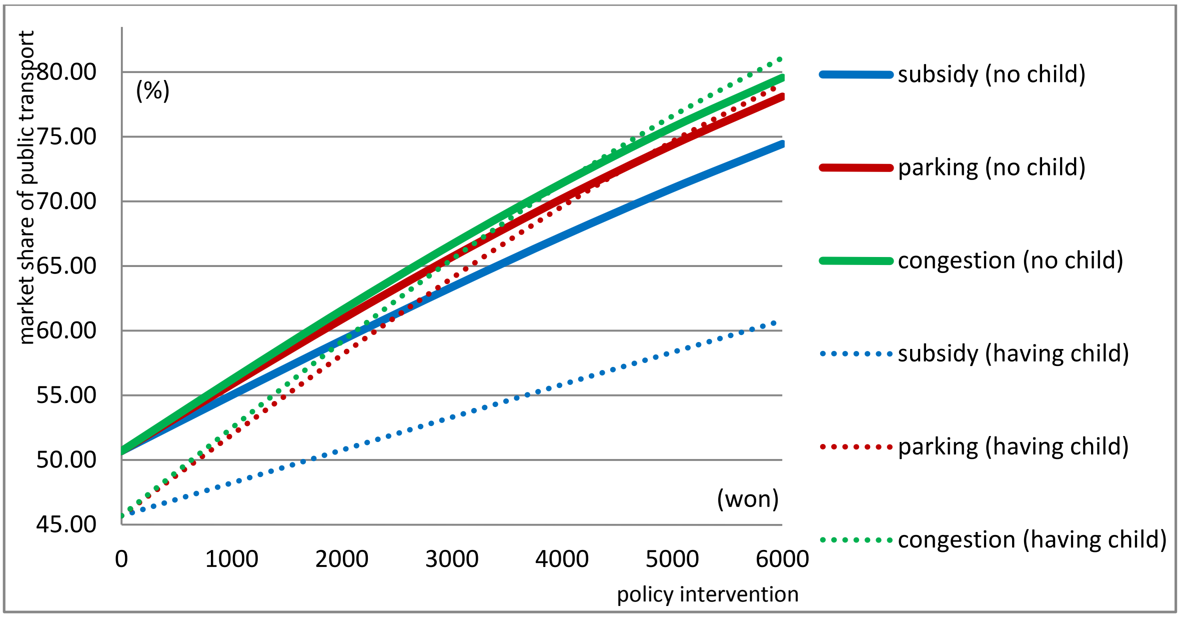
Appendix Table 7-14. Coefficients of segmented models using separate data (Child)

Coefficient		Not having a child or children		Having a child or children	
		Beta	t-value	Beta	t-value
ASC	β_0	-0.0272	-0.5046	**0.1735**	**3.1002****
PT commuting cost subsidy	β_1	**0.1736**	**10.1927****	0.1019	**7.7149****
Additional parking fee	β_2	**-0.2074**	**-15.3266****	**-0.2505**	**-17.7329****
Congestion charge	β_3	**-0.2220**	**-19.2953****	**-0.2718**	**-22.4383****
L(0)		-6342.99		-5956.214	
$L(\widehat{\beta})$		-4308.854		-4022.063	
ρ^2		0.32069		0.32473	
Number of observations		383		377	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Figure 7-12**, the child group is more likely to prefer the use of a car rather than the no-child group. In addition, the modal shift effects of the PT commuting cost subsidies for the child group is much lower than the no-child group. Also, the modal shift effects of the congestion charges and the additional parking fees to the child group are very much stronger than the no-child group.

Appendix Figure 7-12. The market share of PT in the segmented models using separate data (Child)



7. Distance of commute

The distance can be classified into three categories: less than 10km (short-distance group), 10.1~20km (middle-distance group), and more than 20km from home to work (long-distance group). In general, people living in the area close to their workplace might behave differently from people living in the area far from their workplace. Therefore, the distance of the commute can be a main segmentation factor.

(1) The segmentation method using dummy variables

In **Appendix Table 7-15**, the ρ^2 of the segmented model (0.372) is higher than the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with a segmented model is the same as the default model B0. The sign of the ASC (β_0, 0.1661) is positive. The positive ASC suggests that these individuals prefer the use of a car.

Appendix Table 7-15. The coefficients of a segmented model with using dummy variables (Distance)

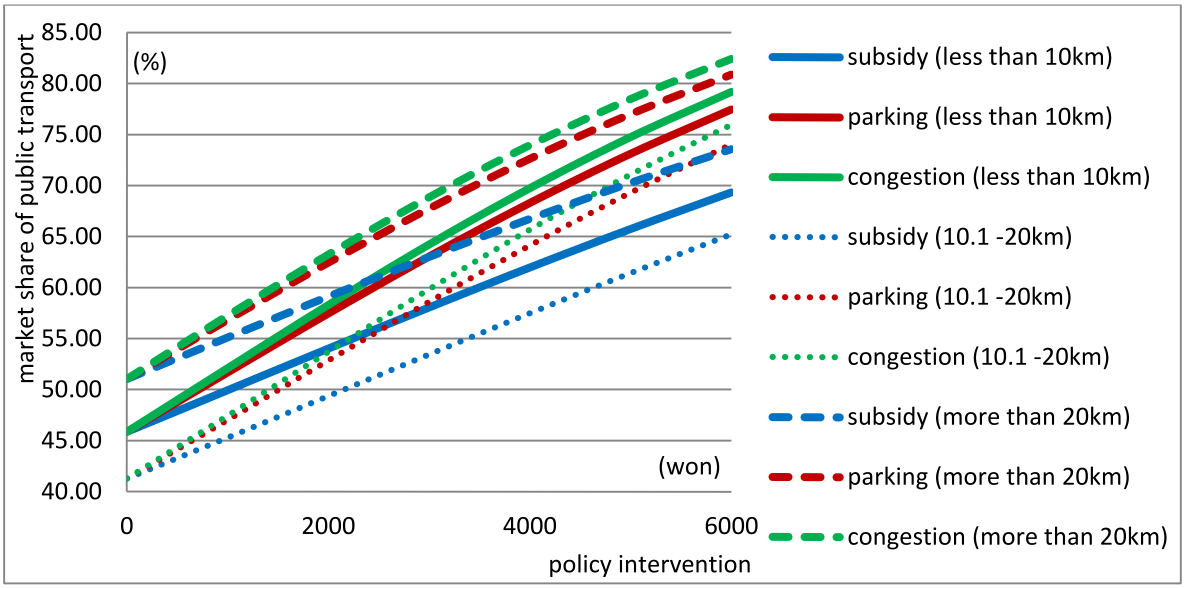
Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**0.1661**	**3.2928****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1636**	**15.6739****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2333**	**-23.0721****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2503**	**-29.0068****
Dummy distance1 (less than 10km:0, 10-20km:1)	$\beta_{distance1}$			**0.1869**	**3.8428****
Dummy distance2 (less than 10km:0, over 20km:1)	$\beta_{distance2}$			**-0.2081**	**-3.9072****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-7792.125	
ρ^2		0.324		0.372	
Number of observations		678		636	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

If a respondent lives in the area at a distance of 10.1 ~ 20km to their workplace (middle-distance group), the value of the dummy attribute (Dummy distance 1) will be one. In this case, the value of the coefficient (0.1869) is multiplied by the value of the attribute (1) (= 0.1869×1). These utility values of the dummy variable (middle-distance group) will be 0.1869. Since the sign of this dummy variable is positive, it is expected that the middle-distance group tends to prefer the use of a car. In addition, if a respondent lives in the area at a distance of more than 20km to their workplace (long-distance group), the value of the dummy attribute (Dummy distance 2) will be one. In this case, the value of the coefficient (– 0.2081) is multiplied by the value of the attribute (1) (= – 0.2081×1). These utility values of the dummy variable (long-distance group) will be – 0.2081. Since the sign of this dummy variable is negative, it is expected that the long distance group tends to prefer the use of PT. Meanwhile, in the specification of a segmented model, the short-distance group are set up as a default value. As a result, if a respondent corresponds to the short-distance group, the value of the dummy attribute will be zero.

All in all, the sign of the coefficient for the dummy variable (– 0.2081) in the long-distance group is negative while the sign of the coefficient for the dummy variable (0.1869) in the middle-distance group is positive. Therefore, since there are various signs of dummy variables, it is difficult to identify a consistent tendency to apply to the distance of commute.

Appendix Figure 7-13. The market share of PT in the segmented model using dummy variables (Distance of commute)



As can be seen in **Appendix Figure 7-13**, the long-distance group seem to favour the use of PT, with the short-distance group expressing their second preference for PT use, and group for PT least preferred use is the middle-distance group. In conclusion, in terms of distance of commute, there is no consistent trend.

(2) Segmentation method using separate data of the segmented groups

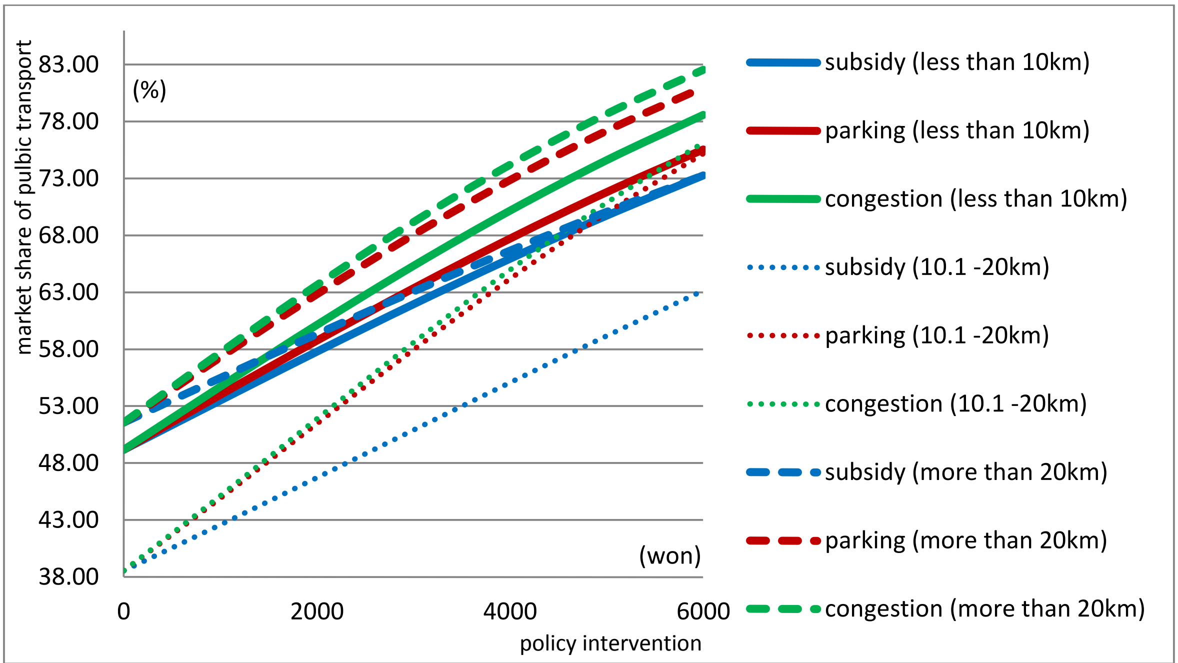
Appendix Table 7-16. The coefficients of segmented models using separate data (Distance of commute)

Classification		Less than 10 km		10.1 ~ 20 km		More than 20 km	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	0.0332	0.4361	**0.4663**	**7.2541****	-0.0621	-0.8486
PT commuting cost subsidy	β_1	**0.1736**	**6.8865****	**0.1674**	**9.8131****	**0.1576**	**10.1466****
Additional parking fee	β_2	**-0.1936**	**-10.3695****	**-0.2624**	**-16.6881****	**-0.2313**	**-12.3390****
Congestion charge	β_3	**-0.2223**	**-13.9633****	**-0.2710**	**-20.2510****	**-0.2487**	**-15.4861****
L(0)		-3135.105		-4511.002		-3993.221	
$L(\widehat{\beta})$		-2215.369		-3204.354		-2366.026	
ρ^2		0.29337		0.28966		0.40749	
Number of observations		194		278		243	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 7-16**, the absolute value (– 0.1936) of the coefficient of the additional parking fee for the short-distance group is lower than that (– 0.2624) of the middle-distance group and that (– 0.2313) of the long-distance group.

Appendix Figure 7-14. The market share of PT in the segmented models using separate data (Distance)



As can be seen in **Appendix Figure 7-14**, the modal shift effects of the PT commuting cost subsidies for the long-distance group is relatively lower than the other groups. Also, the modal shift effects of the congestion charges and additional parking fees for the middle-distance group are very much more significant than the other groups.

8. Information based on the number of cars per household

The number of cars available per household can be a segmented variable since this factor can significantly affect the modal shift effects of MSP. In general, people who have only one car per household (one-car group) might behave differently from people who have several cars (many-car group). Therefore, the number of the car can be a main segmentation factor. The number of cars which a commuter has in their household can be classified into two categories: one car, and two cars or more.

(1) The segmentation method of using a dummy variable

In **Appendix Table 7-17**, the ρ^2 of the segmented model (0.381) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of MSP with the segmented model are the same as those of the default model.

The sign of the coefficient of the ASC (β_0) is negative. The negative ASC means that individuals prefer the use of PT. Considering the sign of the ASC in the default model (model B0), it can be inferred that the inclusion of the dummy variable and the reflection of default value in the specification of the segmented model cause the increase in PT use. Meanwhile, the coefficient of the ASC (β_0) is statistically significant at the 95% level of confidence since the absolute t-value (– 2.3118) is greater than 1.65 and less than 2.57. The positive sign of the coefficient of the dummy variable (0.6618) indicates that the many-car group tends to prefer the use of the car rather than the one-car group.

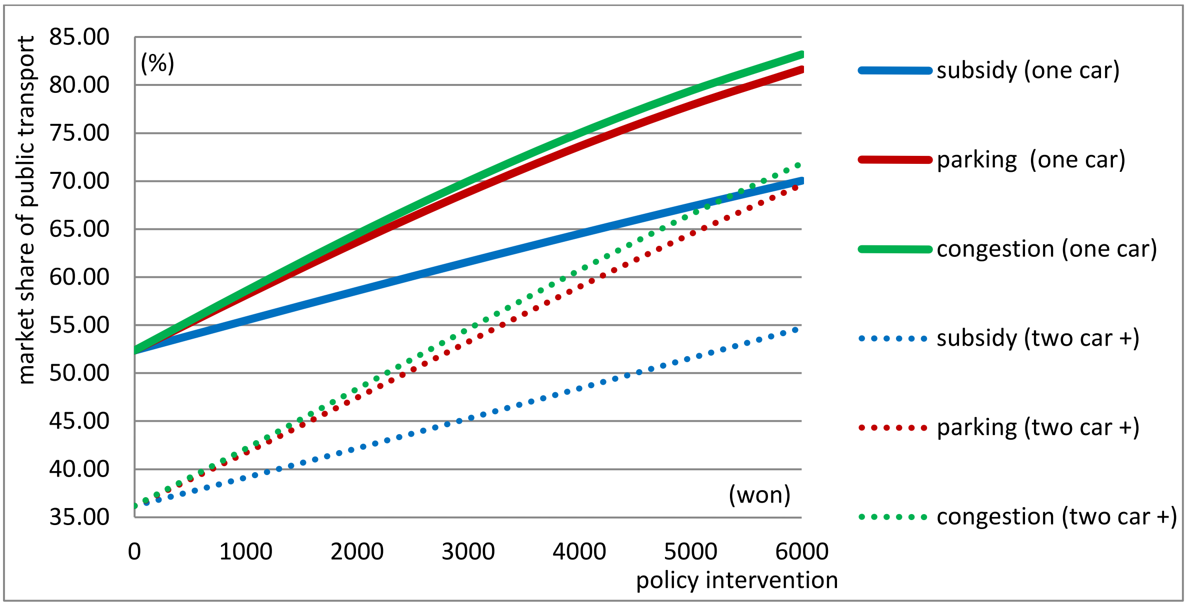
Appendix Table 7-17. The coefficients of a segmented model using a dummy variable (Number of cars)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**-0.0937**	**-2.3118***
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1260**	**13.6799****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2329**	**-23.6419****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2508**	**-29.8237****
Dummy number of car(one car:0, two car+:1)	$\beta_{car\ num}$			**0.6618**	**16.0705****
L(0)		-12405.26		-12405.26	
$L(\widehat{\beta})$		-8389.1		-7675.941	
ρ^2		0.324		0.381	
Number of observations		678		672	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

As can be seen in **Appendix Figure 7-15**, the one-car group tends to use PT rather than the many-car group. This result would seem predictable and logical.

Appendix Figure 7-15. The market share of PT in the segmented model using a dummy variable (Number of cars)



(2) The segmentation method using separate data of the segmented groups

In **Appendix Table 7-18**, all the coefficients (β_1, β_2, and β_3) for the one-car group are higher than the many-car group. It can be inferred that the modal shift effects of the MSP for the one-car group are stronger than the many-car group.

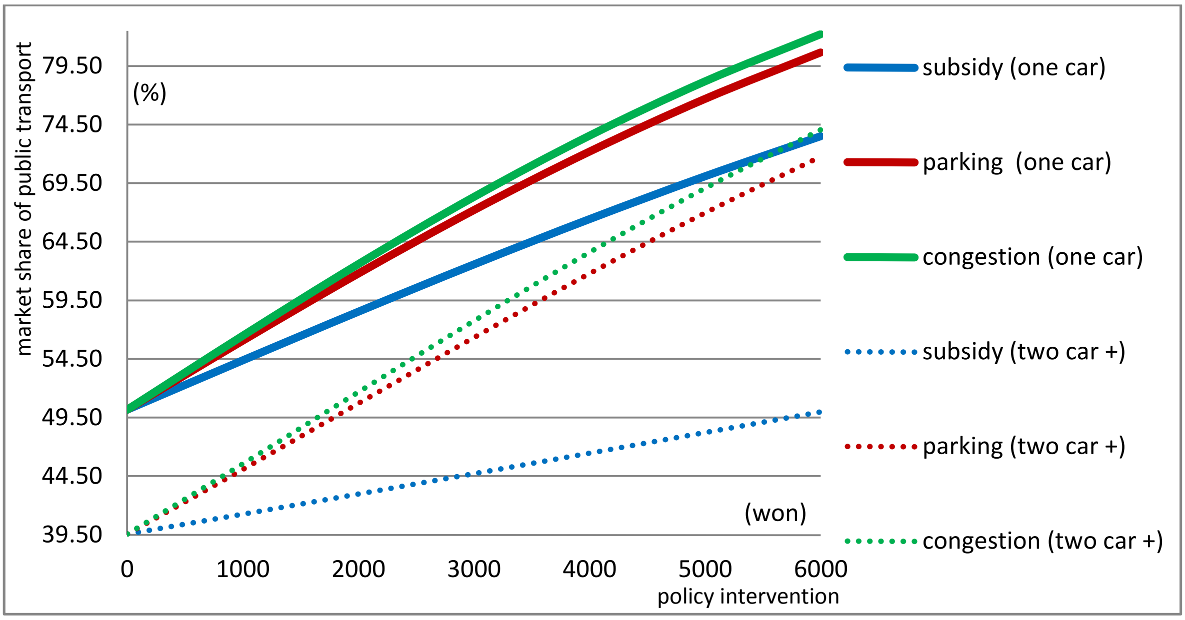
Appendix Table 7-18. The coefficients of segmented models using separate data (Number of cars)

Coefficient		One car		Two cars or more	
		Beta	t-value	beta	t-value
ASC	β_0	-0.0067	-0.1412	**0.4244**	**6.1743****
PT commuting cost subsidy	β_1	**0.1688**	**13.3405****	0.0706	**5.3499****
Additional parking fee	β_2	**-0.2368**	**-19.3345****	**-0.2261**	**-13.6308****
Congestion charge	β_3	**-0.2539**	**-24.1937****	**-0.2454**	**-17.4412****
L(0)		-8828.616		-3495.541	
$L(\widehat{\beta})$		-5475.023		-2740.92	
ρ^2		0.37985		0.21588	
Number of observations		529		232	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Figure 7-16**, the modal shift effects of the PT commute cost subsidies for the many-car group are very much lower than that of the one-car group.

Appendix Figure 7-16. The market share of PT in the segmented models using separate data (Number of cars)



9. Information based on the car commute time

The car commute time can be classified into two categories: less than 40 minutes, and more than 41 minutes. The average commuting time of car users is 46 minutes 24 seconds from the survey. 45 minutes can be used as the classification criterion. In terms of the distribution of samples, the number of car users who take less than 45 minutes commuting time from home to work are 373 (56%) whereas the number of car users who take more than 45 minutes are 293 (44%). However, the number of car users who take less than 40 minutes commuting time from home to work are 318 (47.7%) whereas the number of car users who take more than 41 minutes are 348 (52.3%). Thus, considering the equal allocation ratio of survey samples, this criterion can be acceptable.

Also, the commuting time of car users can be a segmented variable since this factor can affect the modal shift effects of MSP significantly. In general, people who take less than 40 minutes when they use the car (short-time group) might behave differently from people who take more than 41 minutes (long-time group). Therefore, the commuting time of the car can be a main segmentation factor.

(1) The segmentation method using a dummy variable

In **Appendix Table 7-19**, the ρ^2 of the segmented model (0.420) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with the segmented model are the same as those in the default model. The sign of the ASC (β_0) is positive. The positive ASC suggests that individuals prefer the use of a car. Meanwhile, the negative sign of the dummy variable (– 0.1821) indicates that the long-time group tends to prefer the use of PT rather than the short-time group.

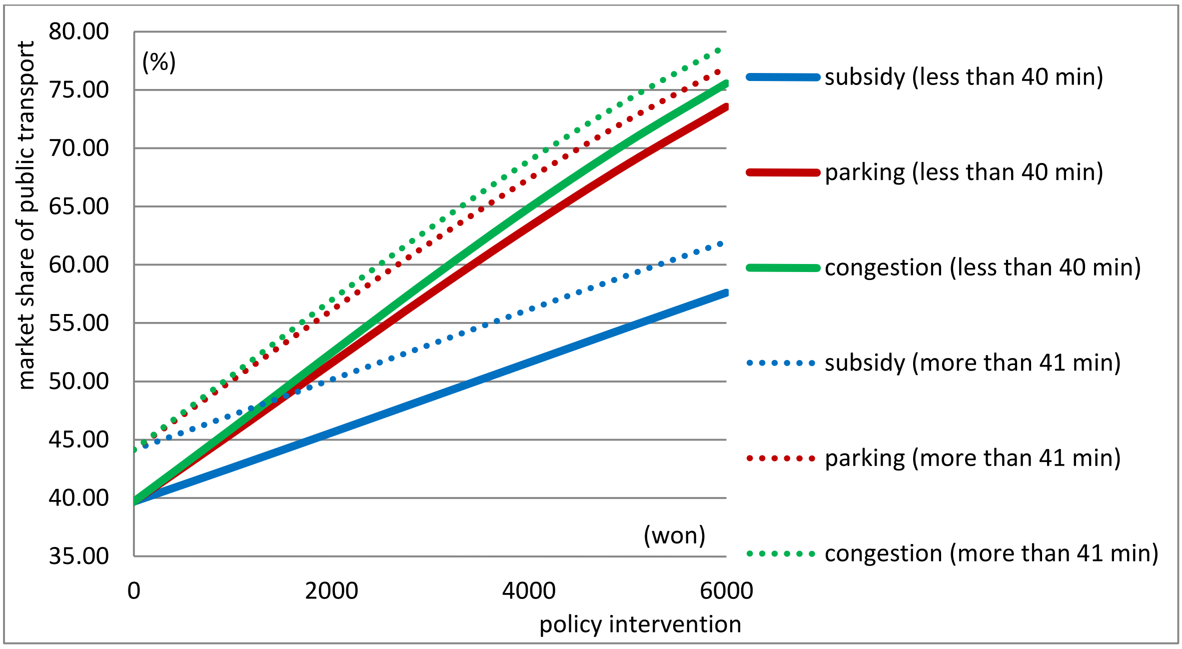
Appendix Table 7-19. The coefficients of a segmented model using a dummy variable (Car commute time)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**0.4182**	**9.2285****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1208**	**12.8759****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2401**	**-23.7930****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2579**	**-29.9793****
Dummy car commute time (less than 40 min:0, over 40 min:1)	$\beta_{car\ time}$			**-0.1821**	**-4.5477****
L(0)		-12405.26		-12405.26	
$L(\widehat{\beta})$		-8389.1		-7191.139	
ρ^2		0.324		0.420	
Number of observations		678		583	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

As can be seen in **Appendix Figure 7-17**, the long-time group tends to use PT more than the short-time group.

Appendix Figure 7-17. The market share of PT in the segmented model of using a dummy variable (Car commute time)



(2) The segmentation method using separate data of the segmented groups

In **Appendix Table 7-20**, the value of the coefficient β_1 (0.0944) for the long-time group is less than that of the short-time group (0.1623).

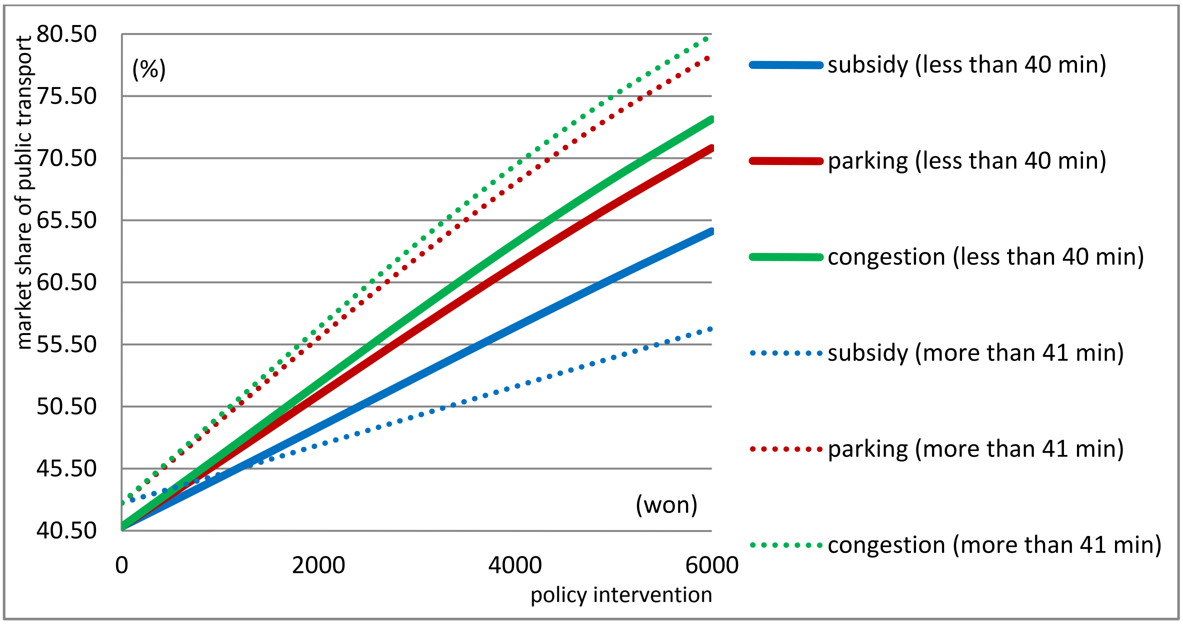
Appendix Table 7-20. The coefficients of segmented models using separate data (Car commute time)

Coefficient		Less than 40 minutes		41 minutes or more	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3714**	**6.3385****	**0.2935**	**5.1159****
PT commuting cost subsidy	β_1	**0.1623**	**10.5418****	**0.0944**	**7.9651****
Additional parking fee	β_2	**-0.2137**	**-15.1345****	**-0.2675**	**-18.4974****
Congestion charge	β_3	**-0.2331**	**-19.4757****	**-0.2841**	**-22.8853****
L(0)		-5039.18		-5665.092	
$L(\widehat{\beta})$		-3808.932		-3852.701	
ρ^2		0.24414		0.31992	
Number of observations		318		348	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

As can be seen in **Appendix Figure 7-18**, the modal shift effects of the PT commuting cost subsidies for the long-time group are very much lower than the short-time group. This result corresponds to the coefficient β_1 in **Appendix Table 7-20**. It means that people who take a long commute time when they use the car are less sensitive to the level of the PT commuting cost subsidy than people who take a short commute time relatively.

Appendix Figure 7-18. The market share of PT in the segmented models using separate data (Car commute time)



10. Information based on the main commuting transport mode

Main commuting transport mode can be a segmented variable since this factor can affect the modal shift effect of MSP significantly. In general, people whose main commuting transport mode is the car (car group) might behave differently from those whose main commuting transport mode is another type, such as bus, train, walk, cycle, taxi, motorcycle and so on (other group). Thus, the main commuting transport mode can be classified into two categories: car and others.

(1) The segmentation method using a dummy variable

In **Appendix Table 7-21**, the ρ^2 of the segmented model (0.420) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of MSP with a segmented model are the same as those of the default model. The sign of the ASC (1.3746) is positive. The positive ASC suggests that individuals prefer the use of a car.

If a respondent belongs to the other group, the value of the dummy attribute will be one. In this case, the coefficient value (– 2.0116) is multiplied by the value of the attribute (= – 2.0116×1). These utility values of the dummy variable (other group) will be – 2.0116. Conversely, if a respondent is affiliated to the car group, the value of the dummy attribute will be zero. That is, the default value of the dummy attributes is set up as the car group. Meanwhile, the negative sign of the dummy variable (– 2.0116) indicates that the other group tends to prefer the use of PT.

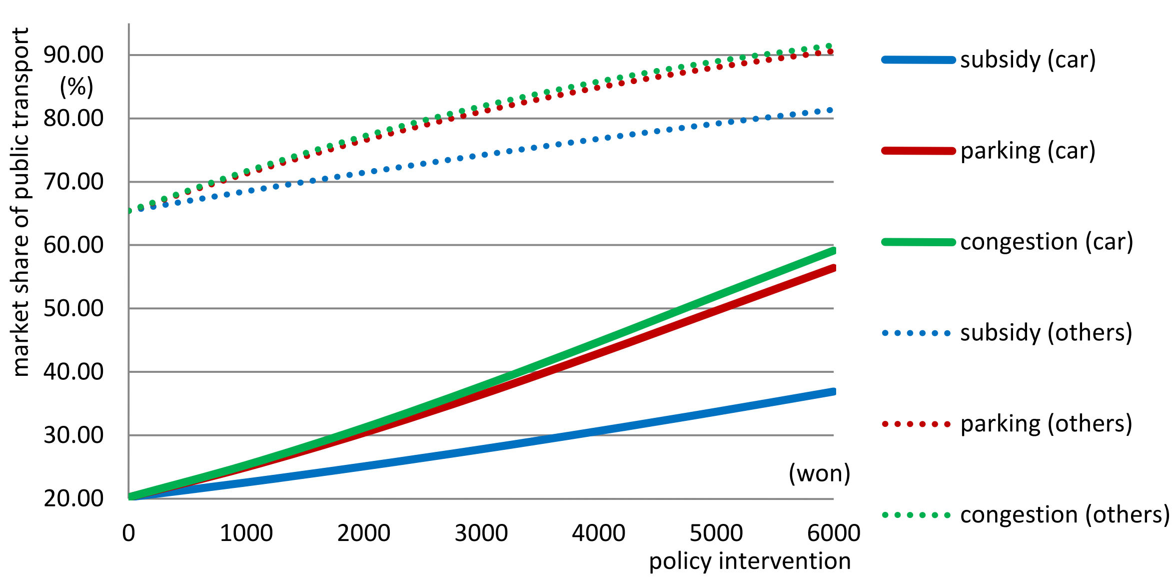
Appendix Table 7-21. The coefficients of a segmented model using a dummy variable (Main commuting transport mode)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**1.3746**	**26.5649****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1398**	**14.1600****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2721**	**-25.3259****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2907**	**-31.5703****
Dummy main commuting transport mode (car user:0, other:1)	$\beta_{main\ mode}$			**-2.0116**	**-45.7287****
L(0)		-12405.26		-12405.26	
$L(\widehat{\beta})$		-8389.1		-7191.139	
ρ^2		0.324		0.420	
Number of observations		678		678	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

As can be seen in **Appendix Figure 7-19**, the car group tends to use the car rather than the other group. The interesting point is that as the level of the policy intervention grows, the slope of congestion charges and additional parking fees for the car group is steeply increasing.

Appendix Figure 7-19. The market share of PT in the segmented model using a dummy variable (Main commuting transport mode)



(2) The segmentation method using separate data of the segmented groups

In **Appendix Table 7-22**, the sign of the ASC coefficient (β_0) for the other group is negative. It implies that the other group prefers PT use rather than the car use. In addition, the value of the coefficient (β_1) (0.1005) for the car group is much lower than the car group (0.2185). It suggests that the modal shift effect of the PT commuting cost subsidies for the car group is weaker than that of the other group.

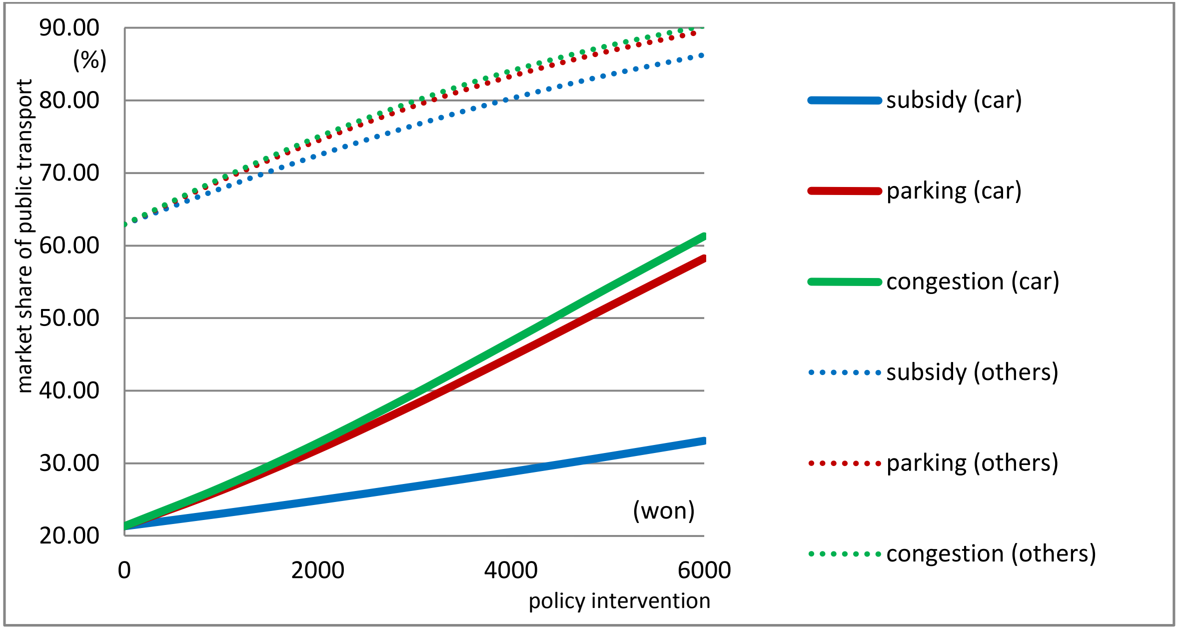
Appendix Table 7-22. The coefficients of segmented models using separate data (Main commuting transport mode)

Coefficient		Car		Others	
		Beta	t-value	beta	t-value
ASC	β_0	**1.3070**	**20.7112****	**-0.5290**	**-8.9637****
PT commuting cost subsidy	β_1	**0.1005**	**8.5156****	**0.2185**	**12.0751****
Additional parking fee	β_2	**-0.2732**	**-19.4781****	**-0.2703**	**-16.1479****
Congestion charge	β_3	**-0.2943**	**-24.7803****	**-0.2838**	**-19.5078****
L(0)		-4474.958		-7930.297	
$L(\widehat{\beta})$		-3789.993		-3385.218	
ρ^2		0.1530662		0.5731285	
Number of observations		312		454	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Figure 7-20**, the overall level of the market share of PT for the other groups is very much higher than the car group. The interesting point is that as the level of policy intervention grows, the slopes of congestion charges and additional parking fees for the car group are steeply increasing.

Appendix Figure 7-20. The market share of PT in the segmented models using separate data (Main commuting transport mode)



11. The purpose of car use

The purpose of car use can be a segmented variable since this factor can affect the modal shift effect of MSP significantly. In general, people whose purpose of car use is commuting to/from office or school (commuting group) might behave differently from those whose purpose of car use is others such as business, shopping or house usage, leisure (e.g. sport and tour), and so on (other group). The purpose of car use can be classified into two categories: commute to the office or school, and others.

(1) The segmentation method using a dummy variable

In **Appendix Table 7-23**, the ρ^2 of the segmented model (0.393) is higher than the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficient of the MSP with a segmented model are the same as those of the default model. The sign of the ASC (β_0) is positive. The positive ASC means that individuals prefer the use of a car.

If a respondent belongs to the other group, the value of the dummy attribute will be one. In this case, the value of the coefficient (– 1.5200) is multiplied by the value of the attribute (1) (= – 1.5200×1). The utility value of the dummy variable (other group) will be – 1.5200. Conversely, if a respondent is affiliated to the commuting group, the value of the dummy attribute will be zero. That is, the default value of the dummy attributes is set up as the commuting group. The negative sign of the coefficient of the dummy variable (– 1.5200) indicates that the other group tends to prefer the use of PT rather than the commuting group.

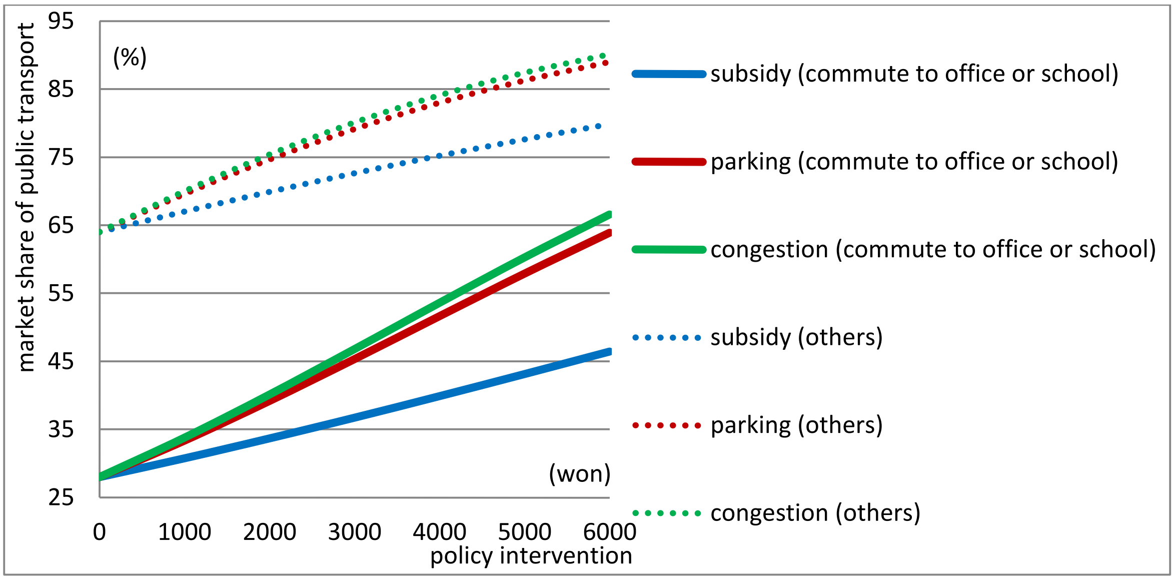
Appendix Table 7-23. The coefficients of a segmented model using a dummy variable (Purpose of car use)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**0.9461**	**19.9370****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1340**	**14.0002****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2527**	**-24.3955****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2724**	**-30.7391****
Dummy purpose of car use (commute:0, others:1)	$\beta_{purpose}$			**-1.5200**	**-35.4219****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-7528.437	
ρ^2		0.324		0.393	
Number of observations		678		653	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

As can be seen in **Appendix Figure 7-21**, the commuting group tends to use a car rather than the other group. This result would seem predictable and logical.

Appendix Figure 7-21. The market share of PT in the segmented model of using a dummy variable (Purpose of car use)



(2) Segmentation method of using separate data of the segmented groups

In **Appendix Table 7-24**, the value of the coefficients β_1 (0.1142) for the commuting group is less than that of the other group (0.1822). That is, the modal shift effects of the PT commuting cost subsidies for the commuting group are relatively low compared to the other group. In addition, an interesting aspect is that the absolute value (– 0.2487) of the coefficient of the additional parking fees (β_2) for the other group is greater than that (– 0.2468) of the congestion charges (β_3).

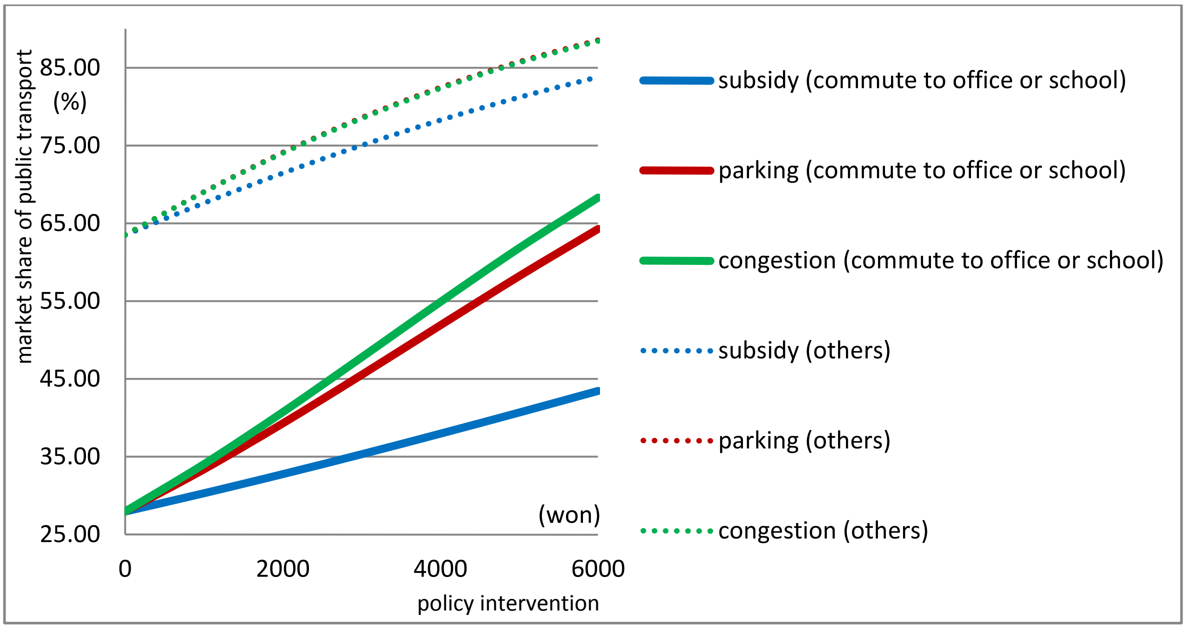
Appendix Table 7-24. The coefficients of segmented models using separate data (Purpose of car use)

Coefficient		Commute to office or school		Others	
		Beta	t-value	beta	t-value
ASC	β_0	**0.9482**	**16.8601****	**-0.5524**	**-8.7936****
PT commuting cost subsidy	β_1	**0.1142**	**10.1062****	**0.1822**	**10.0000****
Additional parking fee	β_2	**-0.2559**	**-19.6819****	**-0.2487**	**-14.4375****
Congestion charge	β_3	**-0.2860**	**-25.8315****	**-0.2468**	**-16.7684****
L(0)		-5480.022		-6520.436	
$L(\widehat{\beta})$		-4444.245		-3076.395	
ρ^2		0.1890		0.5282	
Number of observations		360		382	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Figure 7-22**, the overall level of the market share of PT for the other group is higher than the commuting group. An interesting point is that as the level of policy intervention grows, the slopes of congestion charges and additional parking fees for the commuting group are very steeply increasing.

Appendix Figure 7-22. The market share of PT in the segmented models using separate data (Purpose of car use)



<Reference Data 1>

(1) Segmentation results of the segmented model B2 using socio-economic dummy variables

The deterministic utility function of the segmented model B2 can be expressed as follows:

$$V_{car} = 0.3341 + (-0.3121)\cdot Park_j + (-0.3253)\cdot Congestion_j + 0.0186\cdot Subsidy_j\cdot Park_j$$
$$+ 0.0189\cdot Subsidy_j\cdot Congestion_j + 0.0213\cdot Park_j\cdot Congestion_j$$
$$+ \text{Dummy coefficient 1}\cdot \textit{Dummy attribute 1} + \text{Dummy coefficient 2}\cdot \textit{Dummy attribute 2}$$
$$V_{PT} = 0.2015\cdot Subsidy_j$$

Since model B2 is a model with interaction terms comprising only statistically significant coefficients, the interaction effect of MSPs can be reflected in the calculation of the utility value of travel mode usage. The segmentation analysis of the segmented model B2 using a dummy variable can represent the relative mode preferences across segmented groups. In comparison with **Reference Table 1-1** and **Table 7-5 (page 153)**, the ρ^2 of the segmented model B2 (0.331) is higher than that of the semented model B0 (0.329). It means that the validity of the segmented model with interaction terms is higher than that of the segmented model without interaction terms.

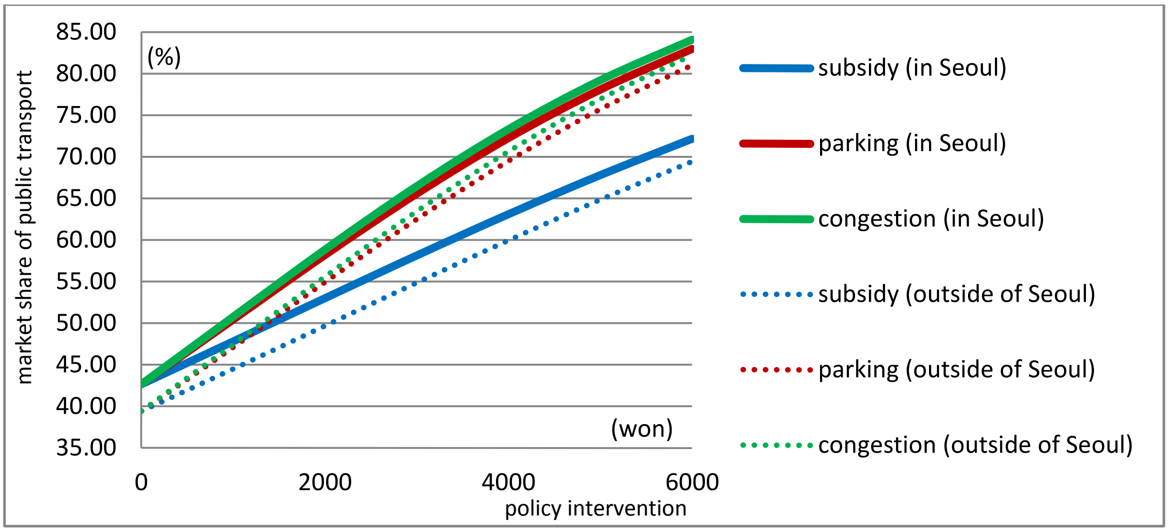
Reference Table 1-1. The coefficients of the segmented model B2 using a dummy variable (Region) (compare **Table 7-5, page 153**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.2973**	**5.7337****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2083**	**12.9396****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3135**	**-19.5853****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3269**	**-23.3956****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0188**	**4.3387****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0191**	**5.0932****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0217**	**5.1653****
Dummy region (In Seoul:0, Outside of Seoul:1)	β_{regoin}			**0.1324**	**3.2987****
L(0)		12405.26		12405.26	
L($\widehat{\beta}$)		8354.584		8293.135	
ρ^2		0.327		0.331	
Number of observations		678		674	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

The results of segmentation analysis in the segmented model B2 using a dummy variable are almost the same as those of the segmented model B0. That is, the position of intercept for each segmented group in the segmented model B2 is almost the same as that of the segmented model B0. In this case, the position of intercept means the relative preferences of travel mode without policy intervention. Also, the sensitivity to the level of MSP across each group in the segmented model B2 is also almost the same as that of the segmented model B0. In other words, although there are small differences between the segmented model B2 and segmented model B0 in the light of magnitude of the modal shift effect of MSP, the order of modal shift effect of the MSP shows almost the same result.

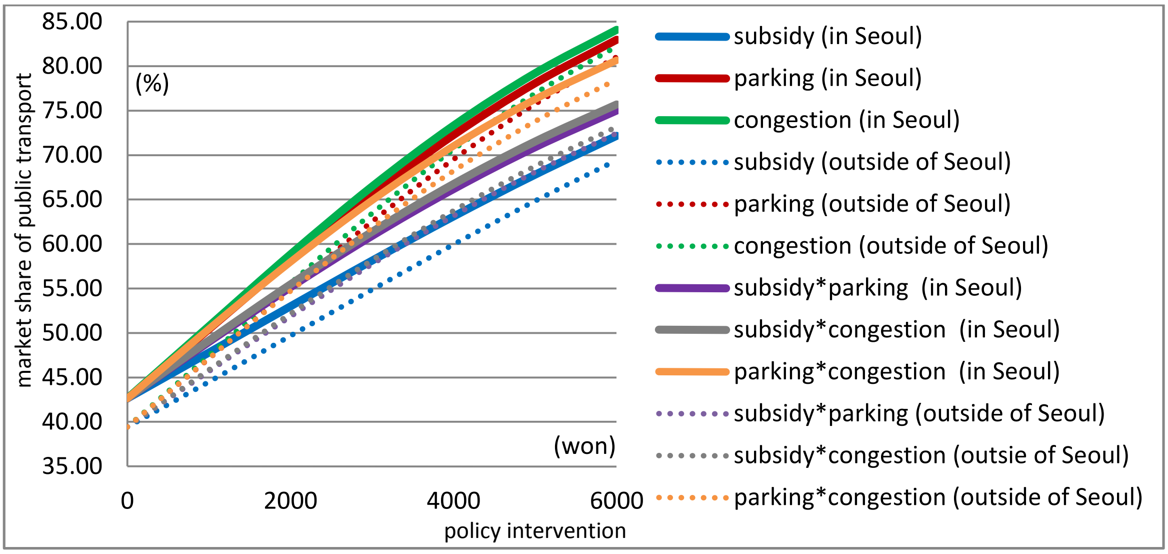
Reference Figure 1-1. The market share of PT in the segmented model B2 of using a dummy variable (Region) (compare **Figure 7-1, page 155**)



For example, as shown in **Reference Figure 1-1**, the position of the intercept of people who live in Seoul is higher than that of people who live outside of Seoul when any policy intervention is not implemented. Like this, as indicated in **Figure 7-1** (**page 155**), the position of intercept for people who live in Seoul is higher than that of people who live outside of Seoul. As a result, the position of the intercept of both models (i.e. the segmented model B2 and the segmented model B0) is similar to each other. Also, the order of modal shift effect of each MSP in **Reference Figure 1-1** is similar to that of **Figure 7-1** (**page 155**). All in all, the results of segmentation analyses for the socio-economic segments in the segmented model B2 are similar to those of the segmented model B0 in terms of the position of intercept and the modal shift effect of the MSP.

Meanwhile, the market share of PT for the combined MSPs is determined according to the sign and the magnitude of the coefficients. For example, the market share of PT for the combination (see the orange line) of additional parking fees (see red the straight line) and congestion charges (see the green straight line) in **Reference Figure 1-2 (page 374)** is similar to that of **Figure 6-16** (see model B2, 'parking + congestion' graphs, **page 140**). Also, the graphs of other combinations between two MSPs in **Reference Figure 1-1** are similar to those of **Figure 6-16 (page 140)**. Since the graphs for the other segmented variables are similar to those of the region factors, the description is omitted. However, the coefficients of the segmented model B2 using dummy variables (**Reference Table 1-2** ~ **Reference Table 1-12**) and the modal shift curves of the MSPs (**Reference Figure 1-3** ~ **Reference Figure 1-13**) are presented.

Reference Figure 1-2. The market share of PT in the segmented model B2 of using a dummy variable (Region), which represents the combined MSP curves



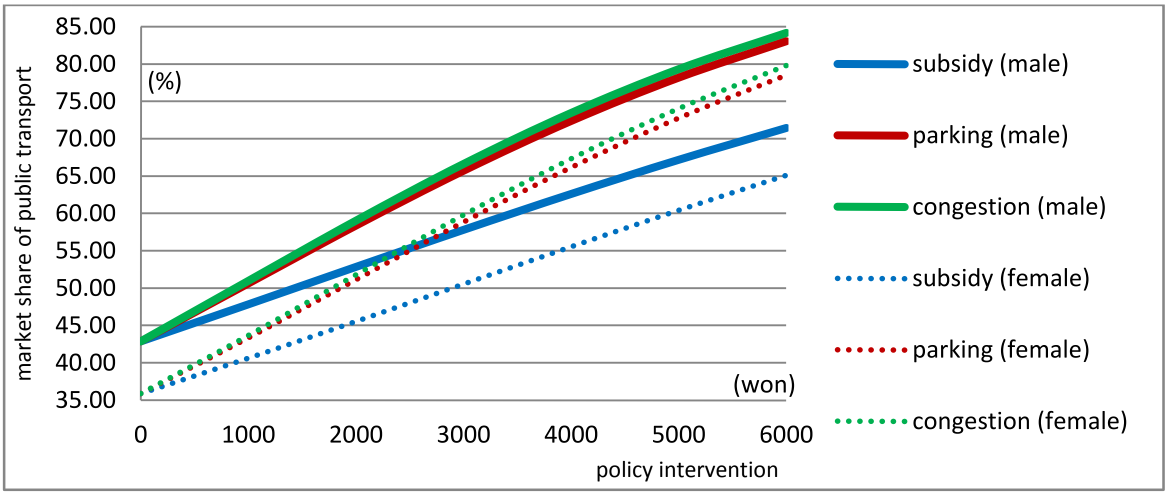
Reference Table 1-2. The coefficients of a segmented model B2 using a dummy variable (Gender) (see **Appendix Table 7-1, page 340**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.2873**	**5.6493****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2006**	**12.5280****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3126**	**-19.5234****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3260**	**-23.3299****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0185**	**4.1660****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0192**	**5.1372****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0217**	**5.1642****
Dummy gender (male:0, female:1)	β_{gender}			**0.2940**	**5.4956****
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-8272.185	
ρ^2		0.327		0.333	
Number of observations		678		672	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 1-3. The market share of PT in the segmented model B2 of using a dummy variable (Gender) (see **Appendix Figure 7-1, page 341**)



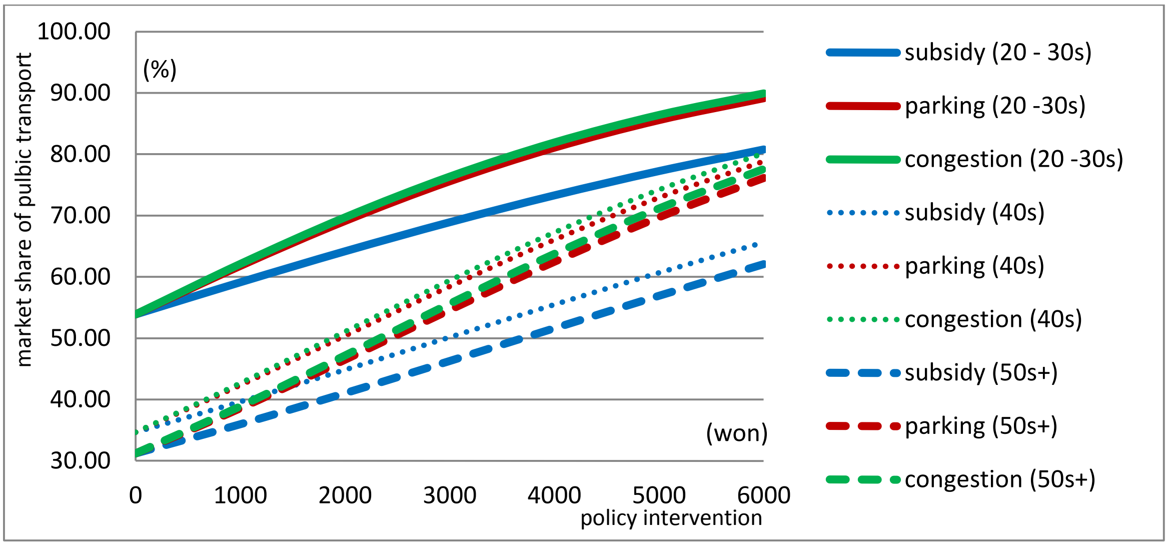
Reference Table 1-3. The coefficients of a segmented model B2 using dummy variables (Age) (see **Appendix Table 7-3, page 344**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**-0.1545**	**-2.7137****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2138**	**13.1794****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3249**	**-19.9489****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3386**	**-23.8204****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0194**	**4.3374****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0205**	**5.4651****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0228**	**5.3294****
Dummy age 1 (20-30s:0, 40s:1)	β_{age1}			**0.7894**	**17.3078****
Dummy age 2 (20-30s:0, 50s+:1)	β_{age2}			**0.9449**	**16.2644****
L(0)		12405.26		-12405.26	
L($\widehat{\beta}$)		8354.584		-8026.982	
ρ^2		0.327		0.353	
Number of observations		678		671	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 1-4. The market share of PT in the segmented model B2 of using dummy variables (Age) (see **Appendix Figure 7-3, page 344**)



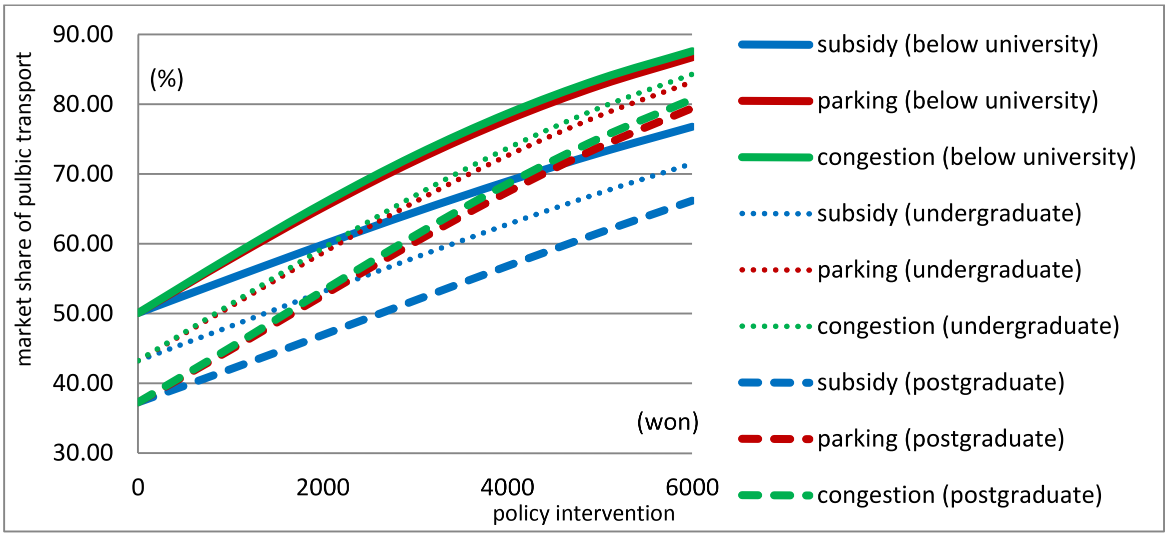
Reference Table 1-4. The coefficients of a segmented model B2 using dummy variables (Education) (see **Appendix Table 7-5, page 347**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	-0.0031	-0.0330
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.1987**	**12.4398****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3121**	**-19.4770****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3255**	**-23.2801****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0183**	**4.1183****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0186**	**4.9771****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0216**	**5.1462****
Dummy education 1 (low edu :0, middle edu :1)	$\beta_{edu\ 1}$			**0.2748**	**3.1430****
Dummy education 2 (low edu :0, high edu :1)	$\beta_{edu\ 2}$			**0.5244**	**5.7764****
L(0)		12405.26		-12405.26	
L($\widehat{\beta}$)		8354.584		-8279.087	
ρ^2		0.327		0.333	
Number of observations		678		673	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 1-5. The market share of PT in the segmented model B2 of using dummy variables (Education) (see **Appendix Figure 7-5, page 347**)



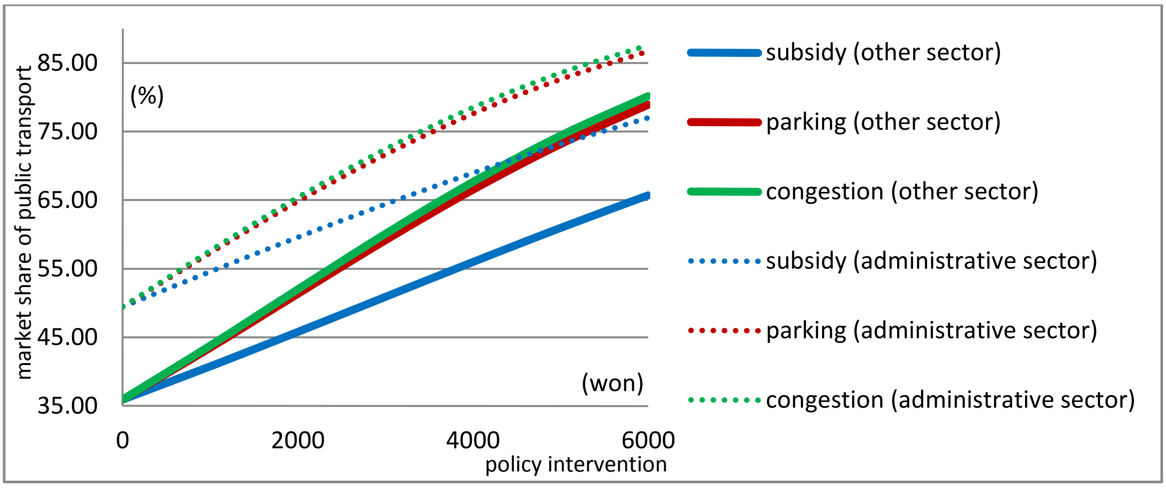
Reference Table 1-5. The coefficients of a segmented model B2 using a dummy variable (Occupation) (see **Appendix Table 7-9, page 350**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.5789**	**10.7462****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2048**	**12.7783****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3161**	**-19.6486****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3291**	**-23.4454****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0185**	**4.1655****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0189**	**5.0494****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0220**	**5.2204****
Dummy occupation (other sectors:0, administrative or clerical sector:1)	β_{work}			**-0.5578**	**-13.7225****
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-8220.47	
ρ^2		0.327		0.337	
Number of observations		678		674	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 1-6. The market share of PT in the segmented model B2 of using a dummy variable (Occupation) (see **Appendix Figure 7-7, page 351**)



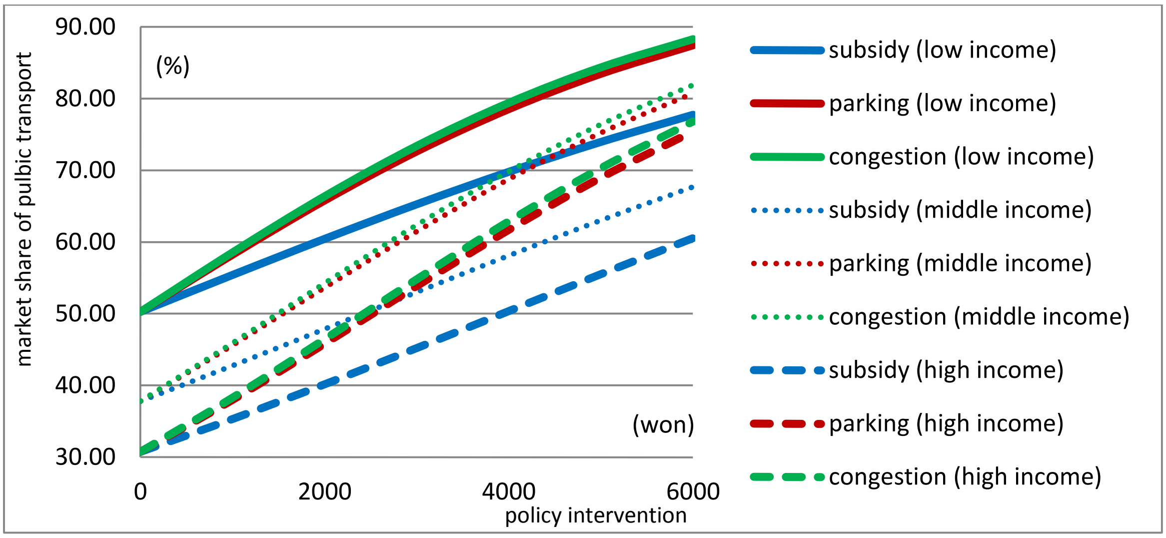
Reference Table 1-6. The coefficients of a segmented model B2 using dummy variables (Income) (see **Appendix Table 7-11, page 353**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	-0.0103	-0.1866
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2066**	**12.7257****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3220**	**-19.8873****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3348**	**-23.7048****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0194**	**4.3113****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0195**	**5.1367****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0229**	**5.4137****
Dummy income 1 (low income:0, middle income:1)	$\beta_{income\ 1}$			**0.5094**	**10.8339****
Dummy income 2 (low income:0,high income:1)	$\beta_{income\ 2}$			**0.8221**	**17.0512****
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-8134.643	
ρ^2		0.327		0.344	
Number of observations		678		675	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 1-7. The market share of PT in the segmented model B2 of using dummy variables (Income) (see **Appendix Figure 7-9, page 354**)



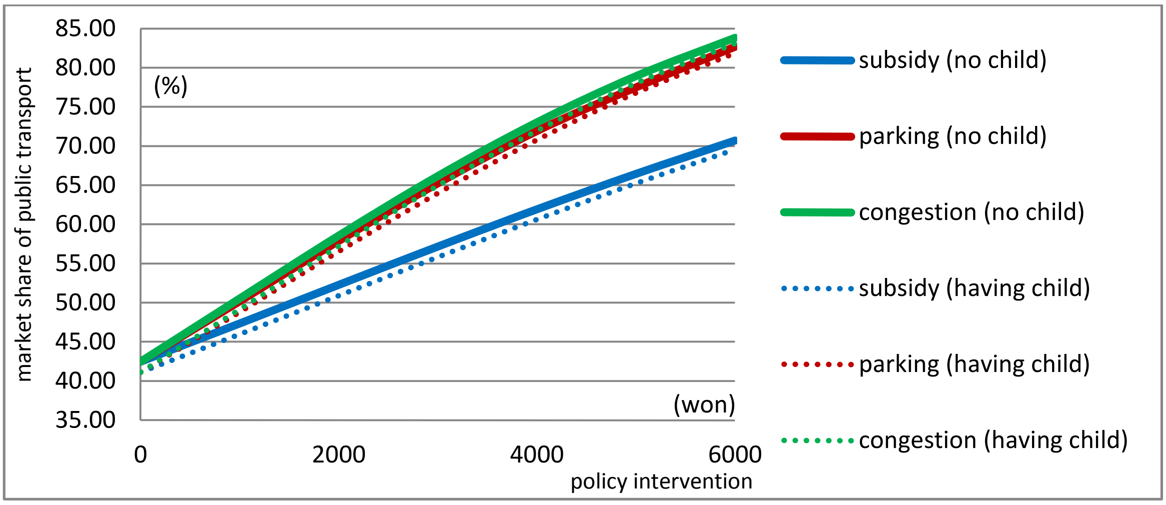
Reference Table 1-7. The coefficients of a segmented model B2 using a dummy variable (Child) (see **Appendix Table 7-13, page 356**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.3044**	**5.6782****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.1976**	**12.3769****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3110**	**-19.4694****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3251**	**-23.3170****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0182**	**4.0962****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0187**	**5.0114****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0215**	**5.1288****
Dummy child (no child: 0, having a child:1)	β_{child}			0.0542	1.3964
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-8305.144	
ρ^2		0.327		0.331	
Number of observations		678		672	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 1-8. The market share of PT in the segmented model B2 of using a dummy variable (Child) (see **Appendix Figure 7-11, page 357**)



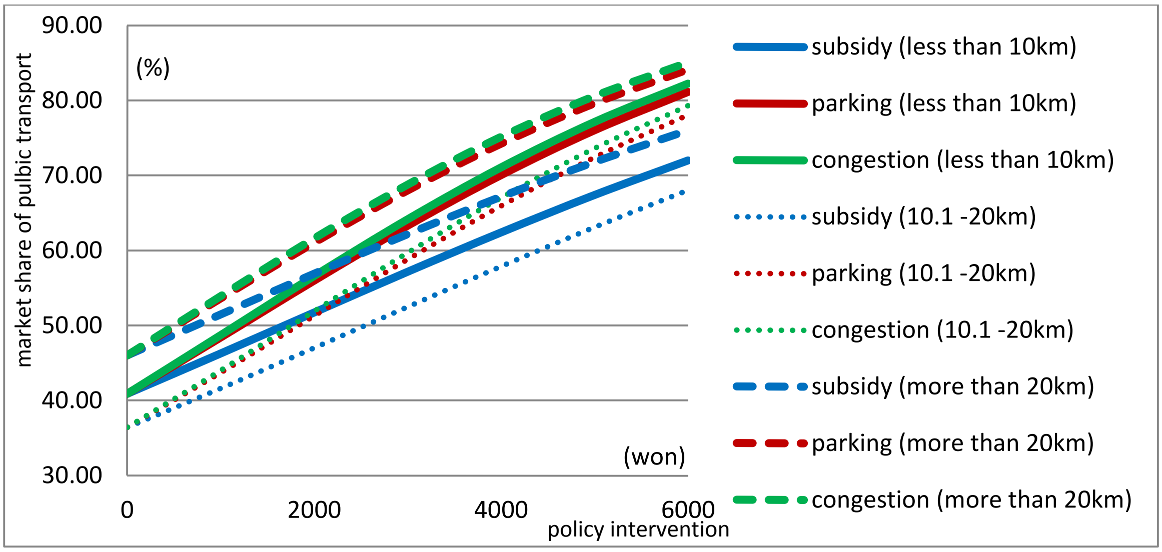
Reference Table 1-8. The coefficients of a segmented model B2 using dummy variables (Commute distance) (see **Appendix Table 7-15, page 359**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.3693**	**6.0707****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2189**	**12.2462****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3045**	**-18.1097****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3168**	**-21.6513****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0129**	**2.4918****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0131**	**2.9856****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0217**	**5.0052****
Dummy distance1 (less than 10km:0, 10-20km:1)	$\beta_{distance1}$			**0.1887**	**3.8600****
Dummy distance2 (less than 10km:0, over 20km:1)	$\beta_{distance2}$			**-0.2085**	**-3.8947****
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-7772.762	
ρ^2		0.327		0.373	
Number of observations		678		636	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 1-9. The market share of PT in the segmented model B2 of using dummy variables (Commute distance) (see **Appendix Figure 7-13, page 360**)

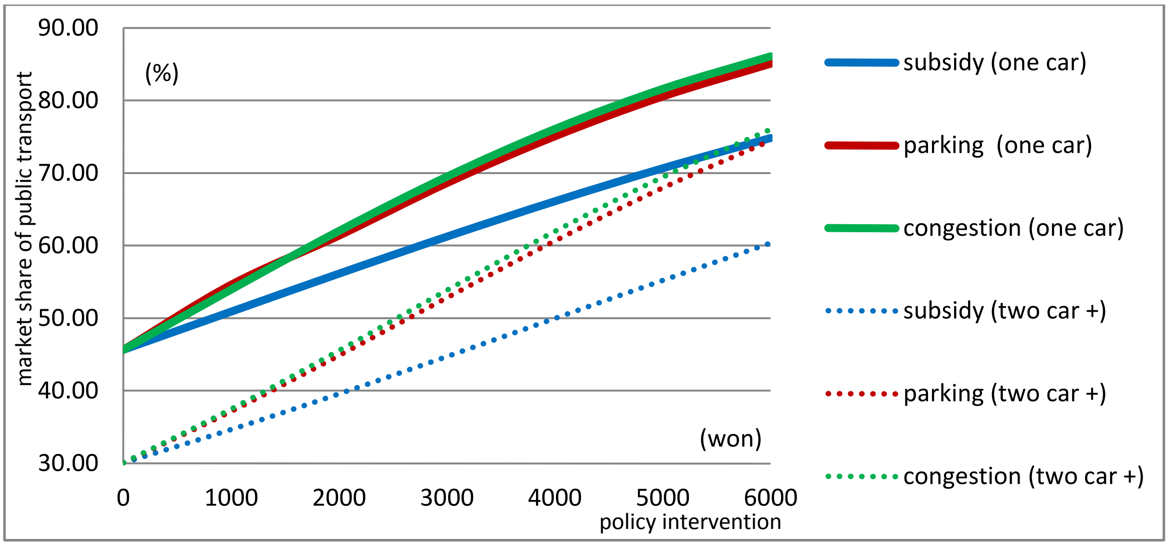


Reference Table 1-9. The coefficients of a segmented model B2 using a dummy variable (Number of cars) (see **Appendix Table 7-17, page 362**)

Coefficient		Model B2 Beta	Model B2 t-value	Segmentation model Beta	Segmentation model t-value
ASC	β_0	**0.3341**	**6.6694****	**0.1755**	**3.3960****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2107**	**13.0916****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3192**	**-19.7981****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3330**	**-23.6722****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0189**	**4.2578****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0194**	**5.1795****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0222**	**5.2592****
Dummy number of car(one car:0, two car+:1)	$\beta_{car\ num}$			**0.6687**	**16.1550****
L(0)		12405.26		-12405.26	
L($\widehat{\beta}$)		8354.584		-8194.498	
ρ^2		0.327		0.339	
Number of observations		678		672	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Reference Figure 1-10. The market share of PT in the segmented model B2 of using a dummy variable (Number of cars) (see **Appendix Figure 7-15, page 363**)

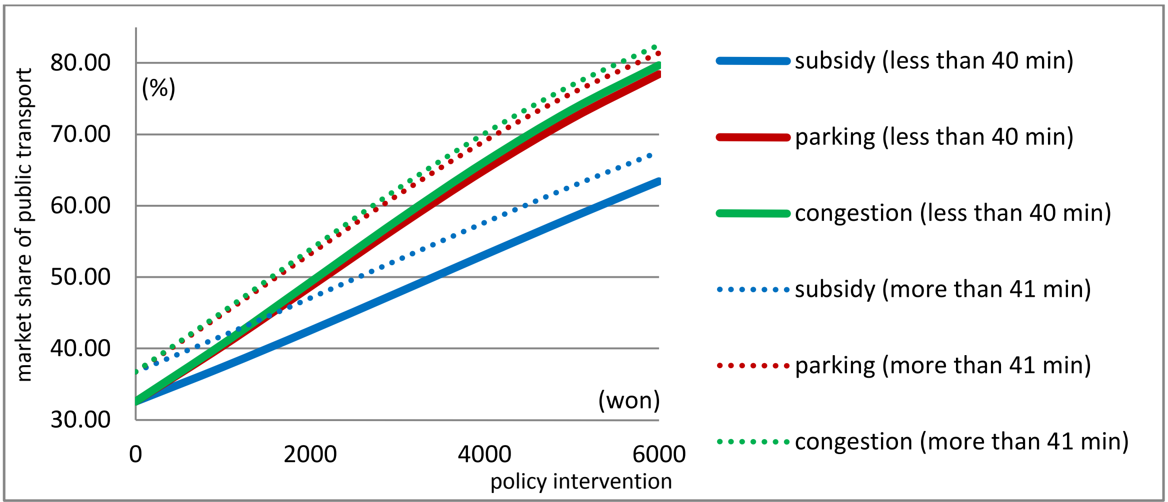


Reference Table 1-10. The coefficients of a segmented model B2 using a dummy variable (Car commute time) (see **Appendix Table 7-19, page 365**)

Coefficient		Model B2 Beta	Model B2 t-value	Segmentation model Beta	Segmentation model t-value
ASC	β_0	**0.3341**	**6.6694****	**0.7280**	**12.6432****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2129**	**12.8882****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3366**	**-20.0979****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3491**	**-23.9749****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0203**	**4.5031****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0207**	**5.4771****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0245**	**5.6799****
Dummy car commute time (less than 40 min:0, over 40 min:1)	$\beta_{car\ time}$			**-0.1834**	**-4.5504****
L(0)		12405.26		-12405.26	
L($\widehat{\beta}$)		8354.584		-7635.872	
ρ^2		0.327		0.384	
Number of observations		678		583	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Reference Figure 1-11. The market share of PT in the segmented model B2 of using a dummy variable (Car commute time) (see **Appendix Figure 7-17, page 365**)

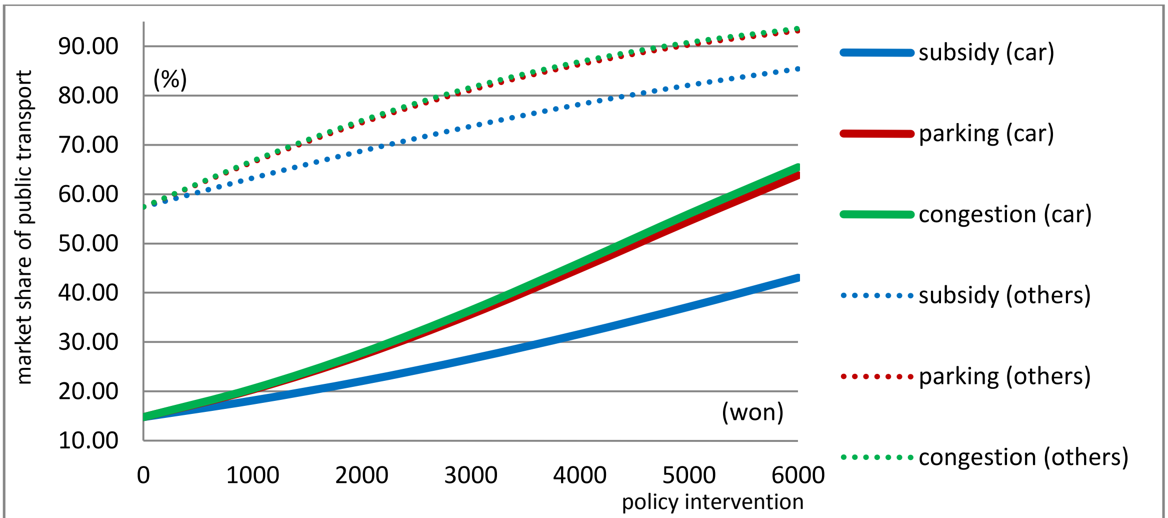


Reference Table 1-11. The coefficients of a segmented model B2 using a dummy variable (Main commuting transport mode) (see **Appendix Table 7-21, page 367**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**1.7521**	**27.0248****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2453**	**14.1644****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3868**	**-21.8942****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3986**	**-25.9285****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0230**	**4.9164****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0234**	**5.9763****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0298**	**6.6081****
Dummy main commuting transport mode (car user:0, other:1)	$\beta_{main\ mode}$			**-2.0499**	**-45.6107****
L(0)		12405.26		-12405.26	
L($\widehat{\beta}$)		8354.584		-7140.427	
ρ^2		0.327		0.424	
Number of observations		678		678	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Reference Figure 1-12. The market share of PT in the segmented model B2 of using a dummy variable (Main commuting transport mode) (see **Appendix Figure 7-19, page 368**)



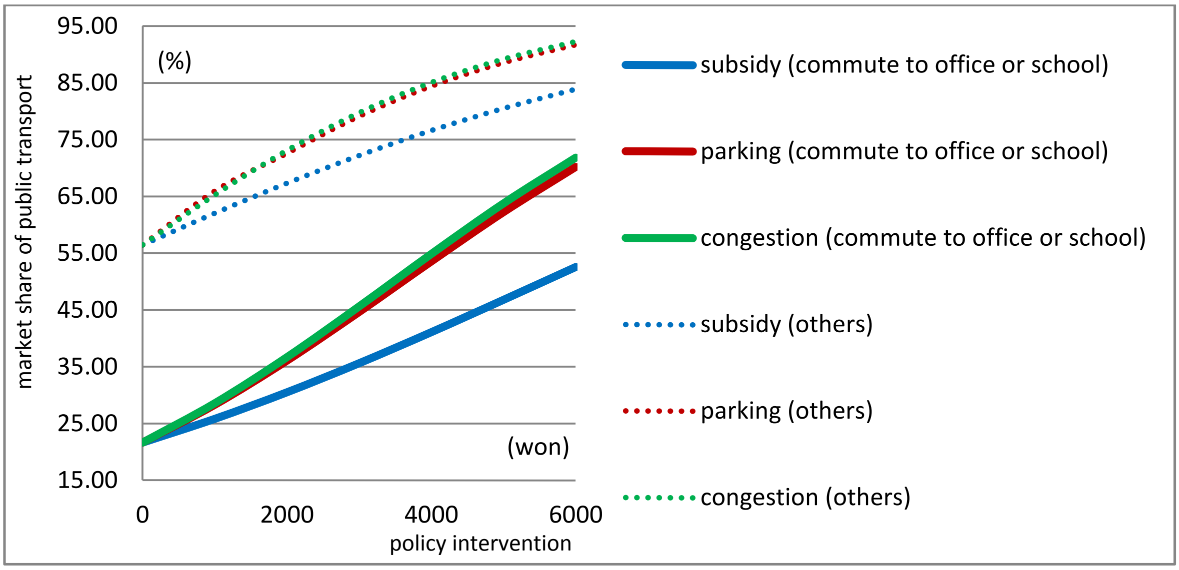
Reference Table 1-12. The coefficients of a segmented model B2 using a dummy variable (Purpose of car use) (see **Appendix Table 7-23, page 370**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**1.2862**	**21.3282****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2316**	**13.7835****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3571**	**-20.8887****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3705**	**-24.8930****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0215**	**4.7013****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0218**	**5.6629****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0269**	**6.1150****
Dummy purpose of car use (commute:0, others:1)	$\beta_{purpose}$			**-1.5465**	**-35.4733****
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-7483.679	
ρ^2		0.327		0.397	
Number of observations		678		653	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 1-13. The market share of PT in the segmented model B2 of using a dummy variable (Purpose of car use) (see **Appendix Figure 7-21, page 370**)



(2) Segmentation results of the segmented model B2 using separate data of segmented groups with socio-economic variables

The results of segmentation analysis using the segmented model B2, which is a model with interaction terms comprising only statistically significant coefficients, with separate data of segmented groups are almost the same as those of the segmented model B0, a model without interaction terms. **Reference Table 2-1** shows the coefficients of segmented models B2 using separate data (Region).

In comparison with **Reference Table 2-1** and **Table 7-7 (page 156)**, the ρ^2 of the segmented models B2 (0.333 and 0.322 respectively) is higher than that of the semented models B0 (0.331 and 0.317 respectively). It means that the validity of the segmented models with interaction terms is higher than that of the segmented models without interaction terms.

Reference Table 2-1. The coefficients of segmented models B2 using separate data (Region)

Coefficient		In Seoul		Outside of Seoul	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3441**	**5.2198****	**0.4024**	**4.9897****
PT commuting cost subsidy	β_1	**0.2631**	**10.0572****	**0.1699**	**8.3302****
Additional parking fee	β_2	**-0.3018**	**-14.4220****	**-0.3319**	**-13.0429****
Congestion charge	β_3	**-0.3166**	**-17.3546****	**-0.3428**	**-15.4368****
Subsidy & Parking	β_{12}	**0.0189**	**2.5439***	**0.0184**	**3.3334****
Subsidy & Congestion	β_{13}	**0.0194**	**3.0724****	**0.0185**	**4.0036****
Parking & Congestion	β_{23}	**0.0195**	**3.5900****	**0.0253**	**3.8201****
L(0)		-7455.491		-4874.904	
L($\widehat{\beta}$)		-4972.918		-3307.461	
ρ^2		0.333		0.322	
Number of observations		466		296	

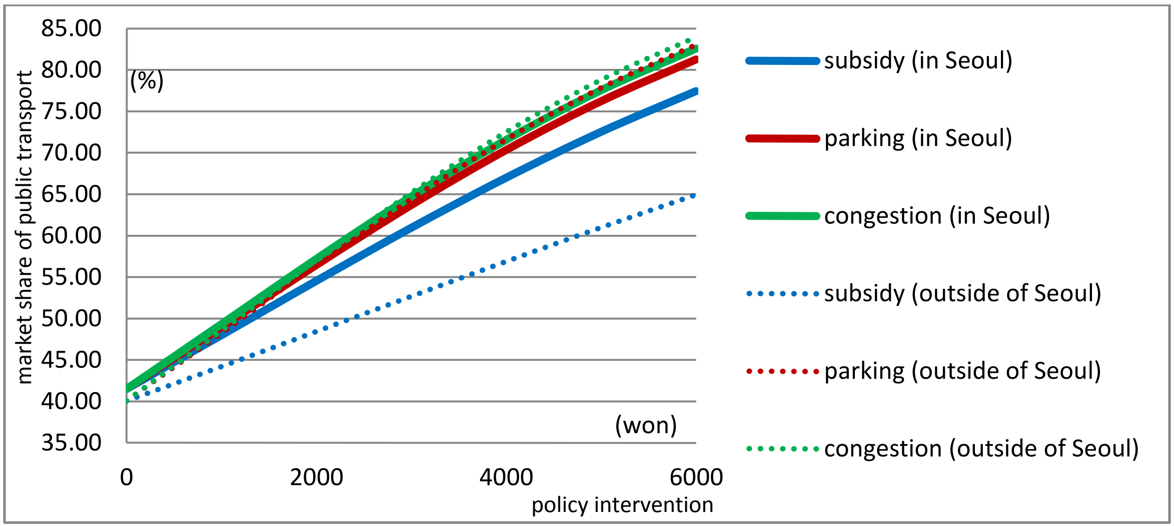
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

The position of the intercept for each segmented group in the segmented model B2 is almost the same as that of the segmented model B0. However, there is one exception. As indicated in **Reference Figure 2-1** (**page 383**), the position of the intercept of people who live in Seoul is higher than that of people who live outside of Seoul (model B2). However, in **Figure 7-2** (**page 158**), the position of the intercept of people who live in Seoul is lower than that of people who live outside of Seoul (model B0). As mentioned in Chapter 7, a drawback of segmentation model using separate data of segmented groups can be the occurrence of the wrong position of intercept. In this case, the position of the intercept of segmented model B0 in **Figure 7-2** (**page 158**) must be wrong. This result indicates that the inclusion of the interaction effect of the MSP into the segmented model may create corrective influence. The position of the intercept in the segmented model B2 with the region variable, as shown in **Reference Figure 2-1**, is similar to that of **Figure 7-1** (**page 155**).

Also, the order of the modal shift effect of each MSP in **Reference Figure 2-1** is similar to that of **Figure 7-2** (**page 158**). That is, the greatest level of modal shift would be achieved by the introduction of congestion charges while the lowest level of modal shift would be obtained by the implementation of PT commuting cost subsidies.

All in all, the results of segmentation analyses for the socio-economic factors in the segmented model B2 are similar to those of the segmented model B0 in terms of the position of the intercept and the modal shift effect of MSP.

Reference Figure 2-1. The market share of PT in the segmented model B2 of using separate data of segmented groups (Region) (see **Figure 7-2, page 158**)

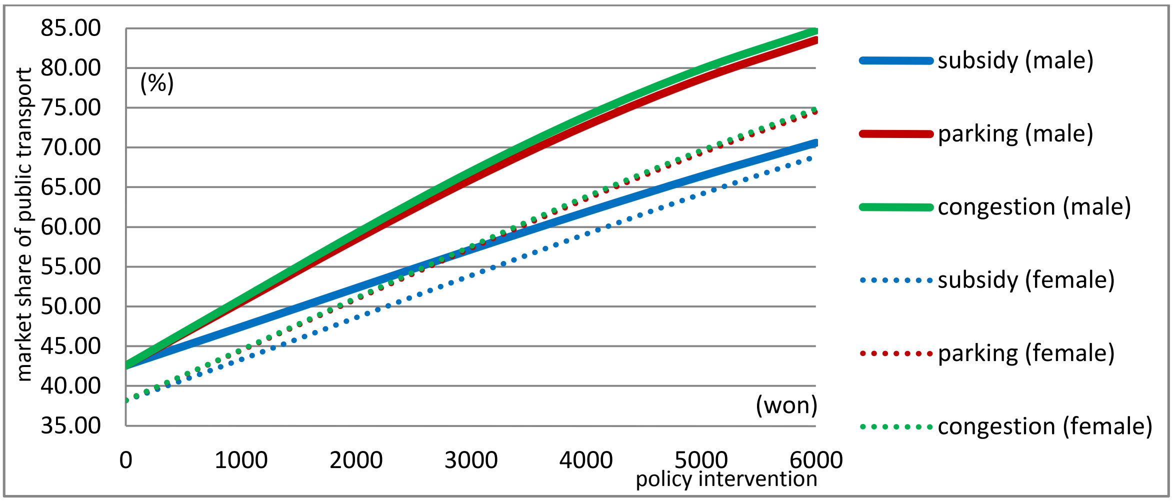


Reference Table 2-2. The coefficients of segmented models B2 using separate data (Gender) (see **Appendix Table 7-2, page 342**)

Coefficient		Male		Female	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.2998**	**5.5519****	**0.4814**	**3.5810****
PT commuting cost subsidy	β_1	**0.1960**	**11.5845****	**0.2124**	**4.7283****
Additional parking fee	β_2	**-0.3205**	**-18.5783****	**-0.2590**	**-6.1863****
Congestion charge	β_3	**-0.3354**	**-22.2235****	**-0.2620**	**-7.2983****
Subsidy & Parking	β_{12}	**0.0203**	**4.3873****	0.0033	0.2495
Subsidy & Congestion	β_{13}	**0.0218**	**5.6495****	-0.0034	-0.2984
Parking & Congestion	β_{23}	**0.0212**	**4.5943****	**0.0209**	**2.0196***
L(0)		-10582.97		-1714.846	
L($\widehat{\beta}$)		-6994.191		-1264.637	
ρ^2		0.339		0.263	
Number of observations		647		113	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 2-2. The market share of PT in the segmented model B2 of using separate data of segmented groups (Gender) (see **Appendix Figure 7-2, page 342**)

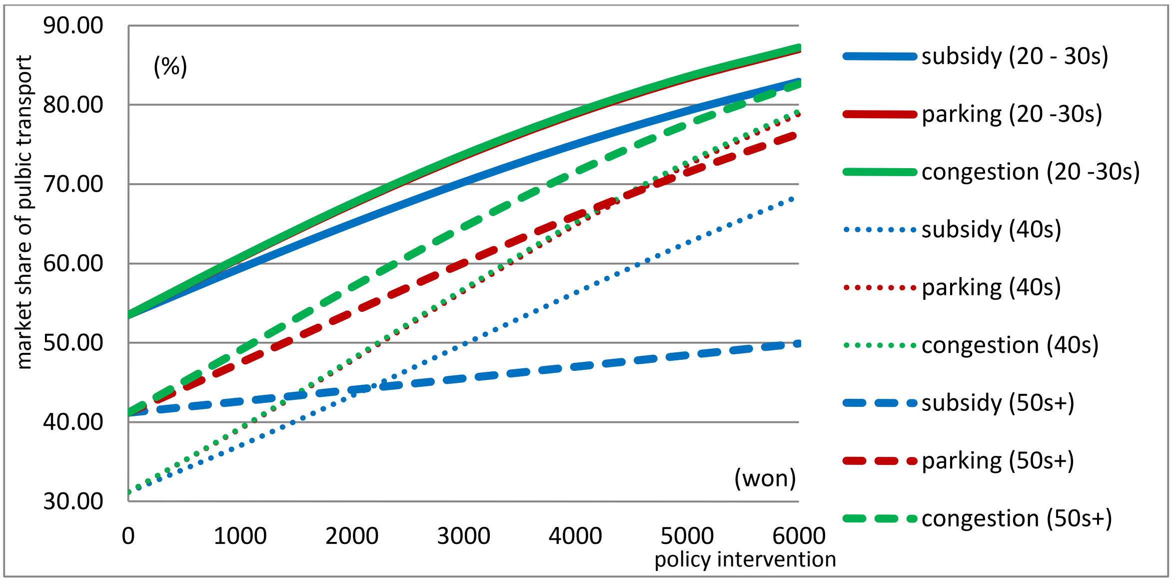


Reference Table 2-3. The coefficients of segmented models B2 using separate data (Age) (see **Appendix Table 7-4, page 345**)

Classification		20-30s (low age group)		40s (middle age group)		50s+ (high age group)	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	-0.1411	-1.6308	**0.7917**	**10.1987****	**0.3559**	**3.1660****
PT commute cost subsidy	β_1	**0.2396**	**7.0286****	**0.2612**	**10.8938****	**0.0587**	**2.3919***
Additional parking fee	β_2	**-0.2935**	**-9.9124****	**-0.3510**	**-14.7007****	**-0.2549**	**-7.3832****
Congestion charge	β_3	**-0.2969**	**-11.4855****	**-0.3547**	**-17.1788****	**-0.3191**	**-10.3500****
Subsidy & Parking	β_{12}	-0.0034	-0.3017	**0.0207**	**3.1053****	**0.0116**	**1.9714***
Subsidy & Congestion	β_{13}	0.0083	0.8947	**0.0197**	**3.4809****	**0.0133**	**2.6936****
Parking & Congestion	β_{23}	**0.0191**	**2.3687***	**0.0283**	**4.6955****	0.0164	1.7325
L(0)		-4874.904		-5466.852		-1938.04	
$L(\widehat{\beta})$		-2565.291		-3900.719		-1503.328	
ρ^2		0.474		0.286		0.224	
Number of observations		283		346		130	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 2-3. The market share of PT in the segmented model B2 of using separate data of segmented groups (Age) (see **Appendix Figure 7-4, page 345**)

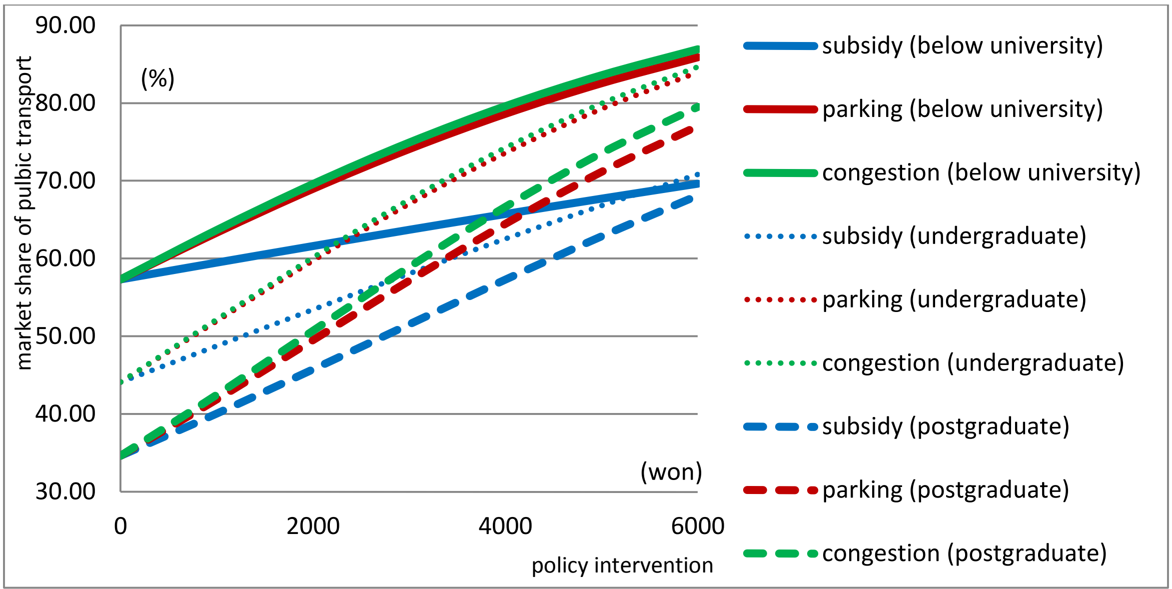


Reference Table 2-4. The coefficients of segmented models B2 using separate data (Education) (see **AppendixTable 7-6, page 348**)

Classification		Below University		Undergraduate		Postgraduate	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	-0.2940	-1.3948	**0.2374**	**3.8544****	**0.6362**	**6.6521****
PT commute cost subsidy	β_1	0.0891	1.2588	**0.1875**	**9.8983****	**0.2324**	**7.4958****
Additional parking fee	β_2	**-0.2521**	**-3.5520****	**-0.3156**	**-15.9971****	**-0.3080**	**-10.4201****
Congestion charge	β_3	**-0.2668**	**-4.2796****	**-0.3242**	**-18.8547****	**-0.3321**	**-12.8886****
Subsidy & Parking	β_{12}	-0.0115	-0.5040	**0.0217**	**4.2821****	0.0105	1.1815
Subsidy & Congestion	β_{13}	-0.0161	-0.8120	**0.0202**	**4.7520****	**0.0165**	**2.2052***
Parking & Congestion	β_{23}	**0.0394**	**2.2060***	**0.0207**	**3.9110****	**0.0201**	**2.6798****
L(0)		-775.6317		-7971.193		-3569.015	
$L(\widehat{\beta})$		-468.9544		-5298.757		-2527.625	
ρ^2		0.395		0.339		0.292	
Number of observations		47		493		222	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 2-4. The market share of PT in the segmented model B2 of using separate data of segmented groups (Education) (see **Appendix Figure 7-6, page 349**)

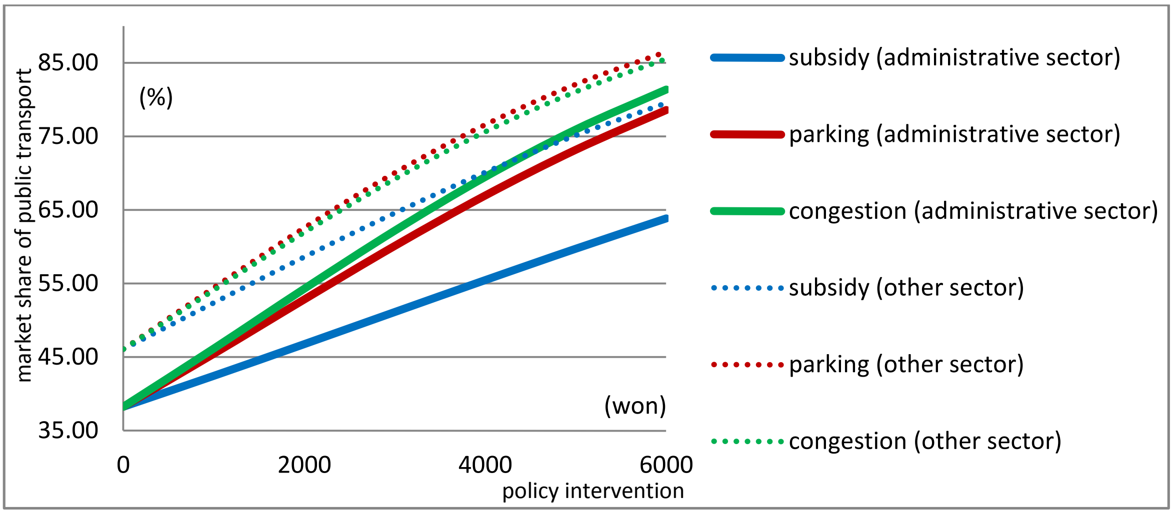


Reference Table 2-5. The coefficients of segmented models B2 using separate data (Occupation) (see **Appendix Table 7-10, page 351**)

Coefficient		Other sectors		Administrative sector	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.4799**	**7.3916****	0.1576	1.9538
PT commuting cost subsidy	β_1	**0.1746**	**9.3172****	**0.2527**	**8.4231****
Additional parking fee	β_2	**-0.2965**	**-14.8278****	**-0.3354**	**-12.3625****
Congestion charge	β_3	**-0.3257**	**-18.5979****	**-0.3221**	**-13.7604****
Subsidy & Parking	β_{12}	**0.0174**	**3.5010****	0.0122	1.3177
Subsidy & Congestion	β_{13}	**0.0191**	**4.6046****	0.0120	1.5322
Parking & Congestion	β_{23}	**0.0203**	**3.9073****	**0.0242**	**3.3494****
L(0)		-7036.83		-5297.031	
$L(\widehat{\beta})$		-5147.487		-3057.606	
ρ^2		0.268		0.423	
Number of observations		444		319	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Reference Figure 2-5. The market share of PT in the segmented model B2 of using separate data of segmented groups (Occupation) (see **Appendix Figure 7-8, page 351**)



Reference Table 2-6. The coefficients of segmented models B2 using separate data (Income) (see **Appendix Table 7-12, page 354**)

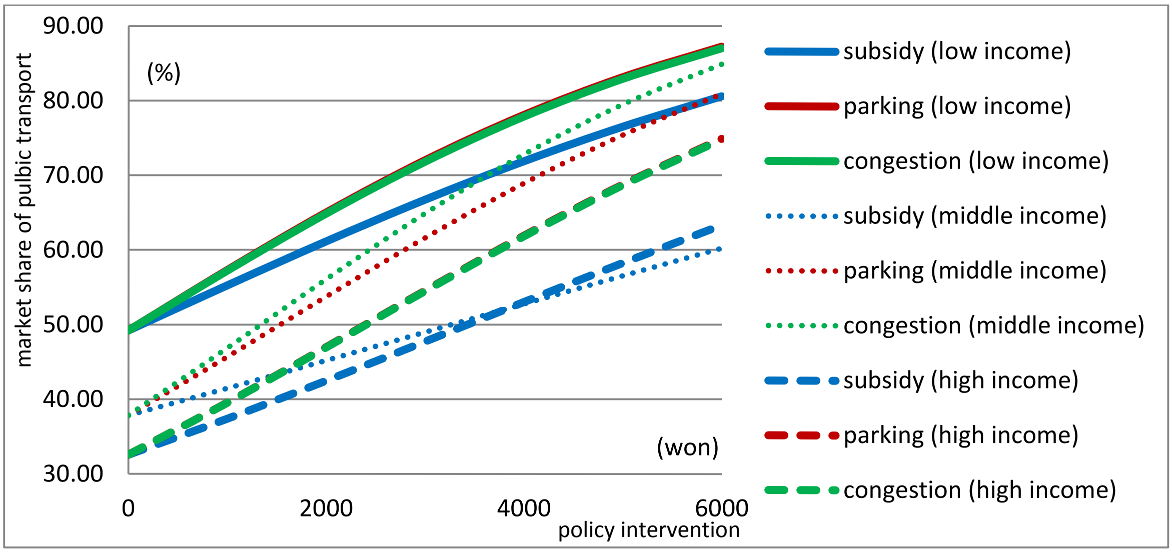
Classification		Low (Up to 5,000t won)		Middle (5,000t ~ 7,000t won)		High (more than 7,000t won)	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	0.0319	0.4126	0.4974	**5.5534****	**0.7283**	**7.1680****
PT commute cost subsidy	β_1	**0.2423**	**8.9853****	**0.1520**	**5.9589****	**0.2123**	**6.5693****
Additional parking fee	β_2	**-0.3254**	**-12.5363****	**-0.3231**	**-11.6716****	**-0.3032**	**-9.8655****
Congestion charge	β_3	**-0.3222**	**-14.2534****	**-0.3703**	**-15.0012****	**-0.3025**	**-11.5153****
Subsidy & Parking	β_{12}	**0.0172**	**2.1514***	**0.0189**	**2.9401****	0.0159	1.8205
Subsidy & Congestion	β_{13}	**0.0168**	**2.4716***	**0.0212**	**4.0067****	**0.0152**	**2.0650***
Parking & Congestion	β_{23}	**0.0275**	**3.9863****	**0.0155**	**1.9989***	**0.0236**	**3.1274****
L(0)		5771.143		3636.25		2945.182	
$L(\widehat{\beta})$		3290.79		2507.173		2314.502	
ρ^2		0.430		0.311		0.214	
Number of observations		343		225		196	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

* Superscript * represents significance within 5%.

Reference Figure 2-6. The market share of PT in the segmented model B2 of using separate data of segmented groups (Income) (see **Appendix Figure 7-10, page 355**)



Reference Table 2-7. The coefficients of segmented models B2 using separate data (Child) (see **Appendix Table 7-14, page 357**)

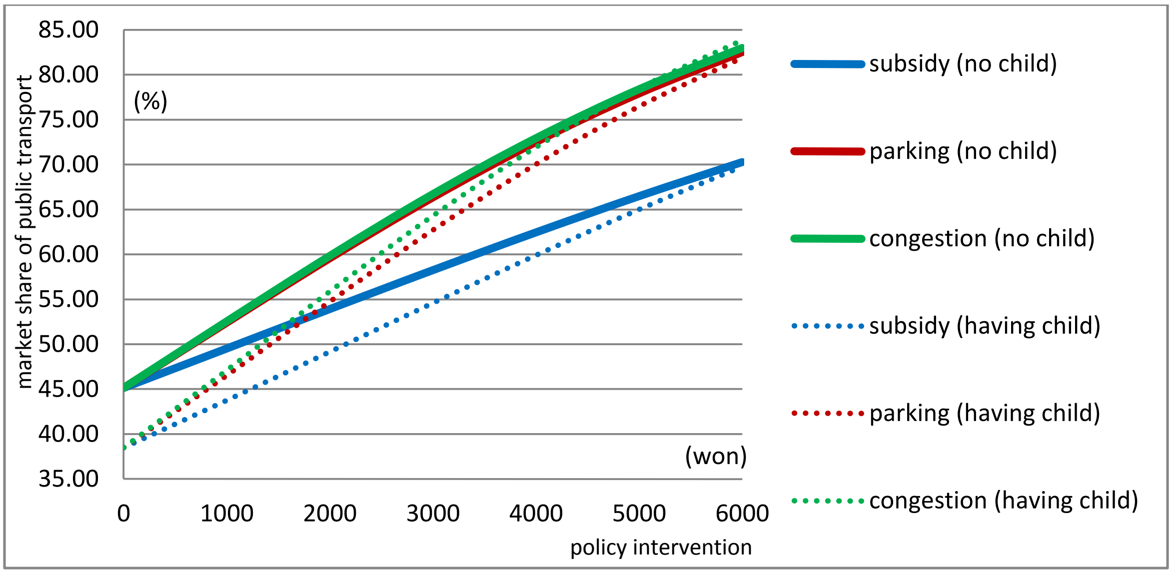
Coefficient		No child		Child	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.1949**	**2.7956****	**0.4695**	**6.5047****
PT commuting cost subsidy	β_1	**0.1758**	**7.9969****	**0.2177**	**9.5617****
Additional parking fee	β_2	**-0.2914**	**-12.9781****	**-0.3296**	**-14.6030****
Congestion charge	β_3	**-0.2968**	**-15.2542****	**-0.3525**	**-17.8118****
Subsidy & Parking	β_{12}	0.0112	1.7780	**0.0242**	**4.0209****
Subsidy & Congestion	β_{13}	0.0098	1.8309	**0.0266**	**5.3465****
Parking & Congestion	β_{23}	**0.0274**	**4.7640****	**0.0142**	**2.3035***
L(0)		-6342.99		-5956.214	
$L(\widehat{\beta})$		-4294.412		-3997.765	
ρ^2		0.323		0.329	
Number of observations		383		377	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

* Superscript * represents significance within 5%.

Reference Figure 2-7. The market share of PT in the segmented model B2 of using separate data of segmented groups (Child) (see **Appendix Figure 7-12, page 358**)



Reference Table 2-8. The coefficients of segmented models B2 using separate data (Commute distance) (see **Appendix Table 7-16, page 361**)

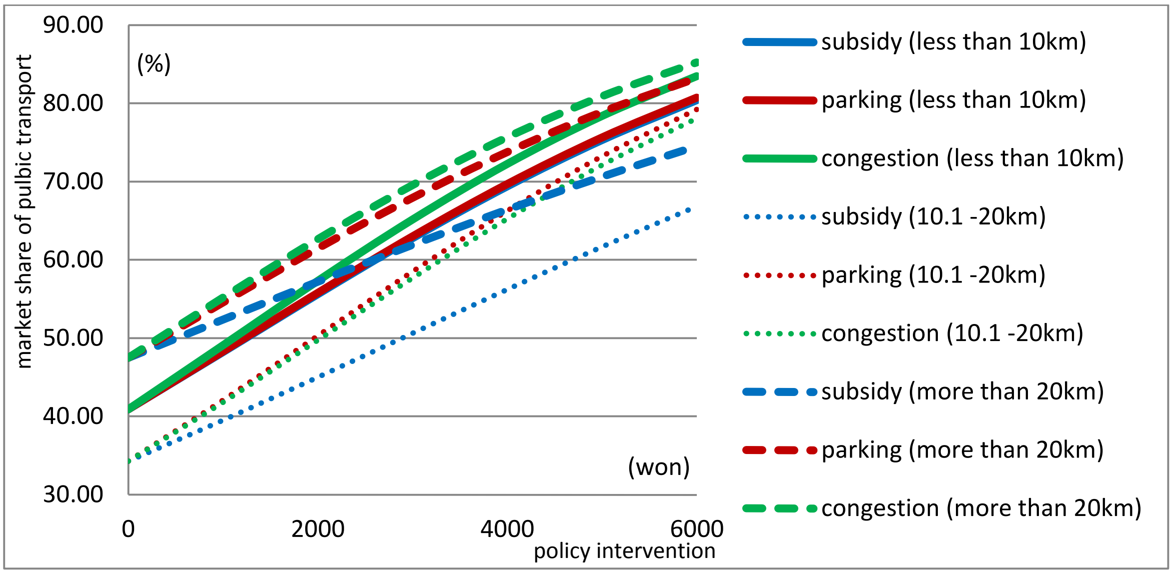
Classification		Less than 10 km		10.1 ~ 20 km		More than 20 km	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**0.3688**	**3.6620****	**0.6515**	**7.6078****	0.1018	1.0811
PT commute cost subsidy	β_1	**0.2967**	**6.5266****	**0.2254**	**7.5801****	**0.1958**	**7.4664****
Additional parking fee	β_2	**-0.3001**	**-9.5866****	**-0.3315**	**-12.4126****	**-0.2840**	**-9.2572****
Congestion charge	β_3	**-0.3314**	**-12.0117****	**-0.3201**	**-14.0009****	**-0.3089**	**-11.4254****
Subsidy & Parking	β_{12}	0.0225	1.8266	**0.0186**	**2.1840***	0.0065	0.8222
Subsidy & Congestion	β_{13}	**0.0299**	**2.9031****	0.0091	1.2446	0.0119	1.7769
Parking & Congestion	β_{23}	**0.0320**	**4.0251****	**0.0167**	**2.4697***	**0.0180**	**2.2248***
L(0)		-3135.105		-4511.002		-3993.221	
$L(\widehat{\beta})$		-2201.287		-3198.556		-2361.814	
ρ^2		0.298		0.291		0.409	
Number of observations		194		278		243	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

* Superscript * represents significance within 5%.

Reference Figure 2-8. The market share of PT in the segmented model B2 of using separate data of segmented groups (Commute distance) (see **Appendix Figure 7-14, page 361**)

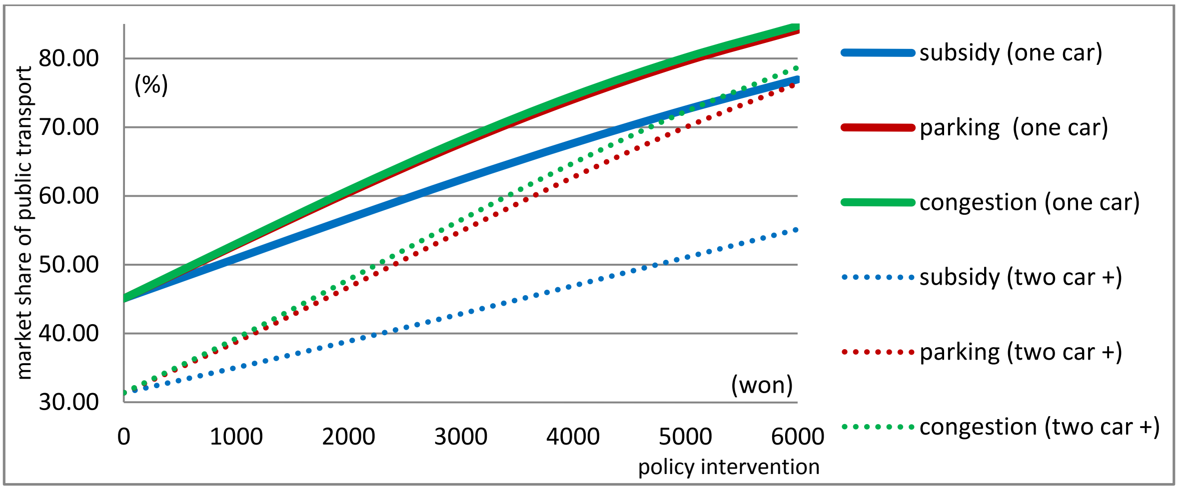


Reference Table 2-9. The coefficients of segmented models B2 using separate data (Number of cars) (see **Appendix Table 7-18, page 363**)

Coefficient		One car		Two cars or more	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.1980**	**3.2407****	**0.7843**	**8.4616****
PT commuting cost subsidy	β_1	**0.2338**	**10.8431****	**0.1651**	**6.8165****
Additional parking fee	β_2	**-0.3113**	**-15.5961****	**-0.3260**	**-11.7960****
Congestion charge	β_3	**-0.3180**	**-18.2501****	**-0.3480**	**-14.5160****
Subsidy & Parking	β_{12}	**0.0177**	**2.8093****	**0.0165**	**2.7058****
Subsidy & Congestion	β_{13}	**0.0139**	**2.5661***	**0.0210**	**4.1760****
Parking & Congestion	β_{23}	**0.0208**	**3.9227****	**0.0253**	**3.5874****
L(0)		-8828.616		-3495.541	
$L(\widehat{\beta})$		-5460.418		-2722.331	
ρ^2		0.382		0.221	
Number of observations		529		232	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 2-9. The market share of PT in the segmented model B2 of using separate data of segmented groups (Number of cars) (see **Appendix Figure 7-16, page 364**)

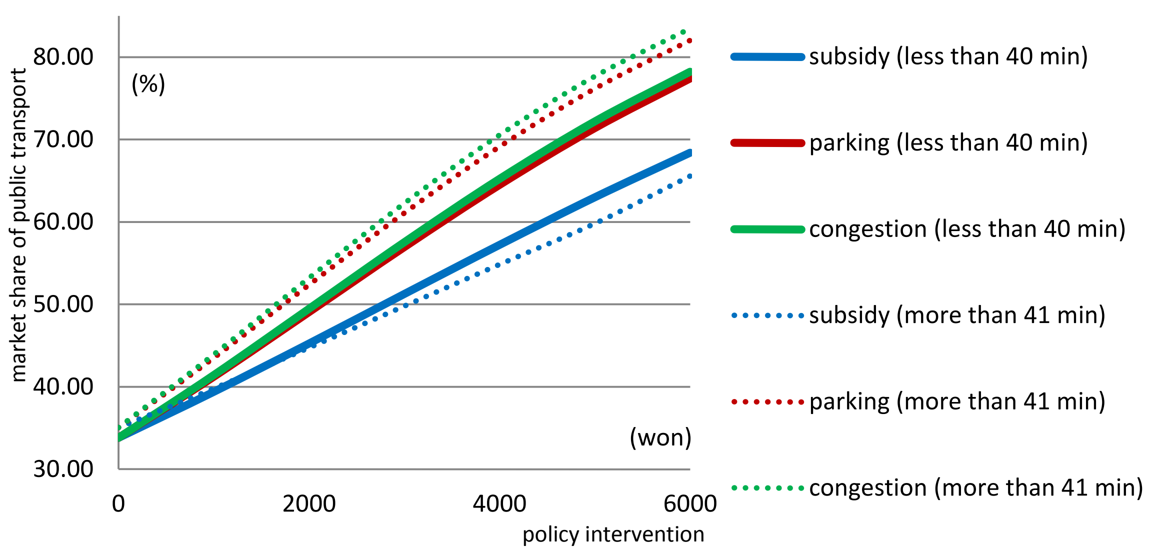


Reference Table 2-10. The coefficients of segmented models B2 using separate data (Car commute time) (see **Appendix Table 7-20, page 366**)

Coefficient		Less than 40 minutes		41 minutes or more	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.6718**	**8.5291****	**0.6179**	**8.2787****
PT commuting cost subsidy	β_1	**0.2407**	**8.6969****	**0.2029**	**9.9144****
Additional parking fee	β_2	**-0.3171**	**-13.1474****	**-0.3559**	**-15.3018****
Congestion charge	β_3	**-0.3252**	**-15.6373****	**-0.3726**	**-18.2997****
Subsidy & Parking	β_{12}	**0.0180**	**2.3628***	**0.0233**	**4.2669****
Subsidy & Congestion	β_{13}	**0.0162**	**2.5249***	**0.0250**	**5.5109****
Parking & Congestion	β_{23}	**0.0303**	**5.0714****	**0.0160**	**2.5384***
L(0)		-5039.18		-5665.092	
$L(\widehat{\beta})$		-3790.56		-3826.005	
ρ^2		0.248		0.325	
Number of observations		318		348	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 2-10. The market share of PT in the segmented model B2 of using separate data of segmented groups (Car commute time) (see **Appendix Figure 7-18, page 366**)

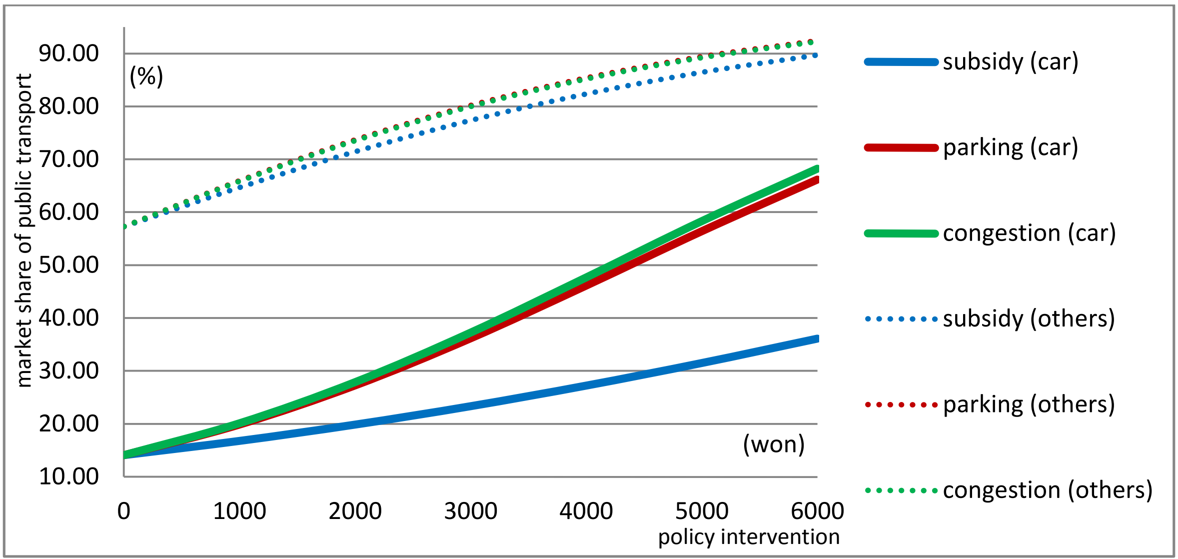


Reference Table 2-11. The coefficients of segmented models B2 using separate data (Main commute mode) (see **Appendix Table 7-22, page 368**)

Coefficient		Car		Others	
		Beta	t-value	Beta	t-value
ASC	β_0	**1.8069**	**19.5372****	**-0.2927**	**-4.0997****
PT commuting cost subsidy	β_1	**0.2061**	**9.1072****	**0.3116**	**10.6660****
Additional parking fee	β_2	**-0.4129**	**-16.3399****	**-0.3684**	**-14.1972****
Congestion charge	β_3	**-0.4283**	**-19.7893****	**-0.3636**	**-15.8184****
Subsidy & Parking	β_{12}	**0.0183**	**3.3059****	**0.0302**	**3.3393****
Subsidy & Congestion	β_{13}	**0.0223**	**4.8358****	**0.0198**	**2.5112***
Parking & Congestion	β_{23}	**0.0359**	**6.0462****	**0.0281**	**3.7591****
L(0)		-4474.958		-7930.297	
$L(\widehat{\beta})$		-3757.295		-3368.987	
ρ^2		0.160		0.575	
Number of observations		312		454	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Reference Figure 2-11. The market share of PT in the segmented model B2 of using separate data of segmented groups (Main commute mode) (see **Appendix Figure 7-20, page 369**)



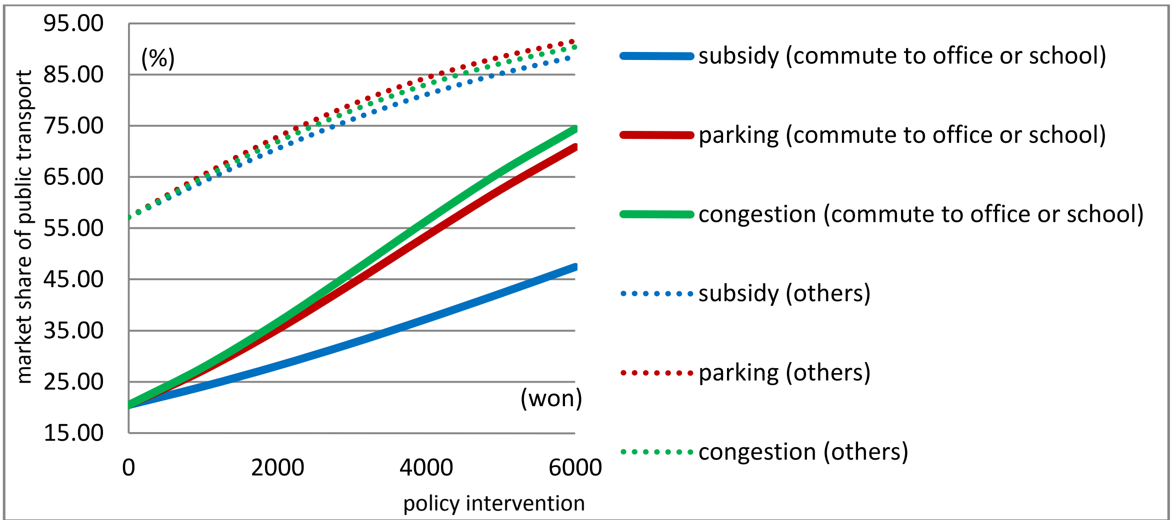
Reference Table 2-12. The coefficients of segmented models B2 using separate data (Purpose of car use) (see **Appendix Table 7-24, page 371**)

Coefficient		Commute to office or school		Others	
		Beta	t-value	Beta	t-value
ASC	β_0	**1.3571**	**17.2033****	**-0.2872**	**-3.7261****
PT commuting cost subsidy	β_1	**0.2092**	**10.1020****	**0.2929**	**9.5040****
Additional parking fee	β_2	**-0.3741**	**-16.5502****	**-0.3490**	**-12.8401****
Congestion charge	β_3	**-0.4037**	**-20.5863****	**-0.3254**	**-13.8759****
Subsidy & Parking	β_{12}	**0.0172**	**3.1965****	**0.0330**	**3.6948****
Subsidy & Congestion	β_{13}	**0.0219**	**4.8682****	**0.0222**	**2.9103****
Parking & Congestion	β_{23}	**0.0319**	**5.7658****	**0.0233**	**3.0834****
L(0)		-5480.022		-6520.436	
$L(\widehat{\beta})$		-4412.845		-3059.971	
ρ^2		0.195		0.531	
Number of observations		360		382	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 2-12. The market share of PT in the segmented model B2 of using separate data of segmented groups (Purpose of car use) (see **Appendix Figure 7-22, page 371**)



Appendix 8. Detailed Result of the Segmentation Analysis with Attitudinal Variables

1. Results of segmentation: Attitude about "the use of PT is important to reduce global warming and to protect the environment."

(1) Segmentation method using dummy variables

In **Appendix Table 8-1**, the ρ^2 of the segmented model (0.363) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP in the segmented model are the same as those of the default model. Since the sign of the ASC (β_0) is negative, it can be interpreted that individuals prefer the use of PT.

Appendix Table 8-1. The coefficients of a segmented model using dummy variables (Environmental consciousness)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**-0.6088**	**-12.2733****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1213**	**12.8944****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2400**	**-23.8232****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2573**	**-29.9204****
Dummy consciousness of environment 1 (strongly agree:0, agree:1)	β_{env1}			**1.0696**	**22.7075****
Dummy consciousness of environment 2 (strongly agree:0, neutral or others:1)	β_{env2}			**1.1934**	**19.9902****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-7898.545	
ρ^2		0.324		0.363	
Number of observations		678		665	

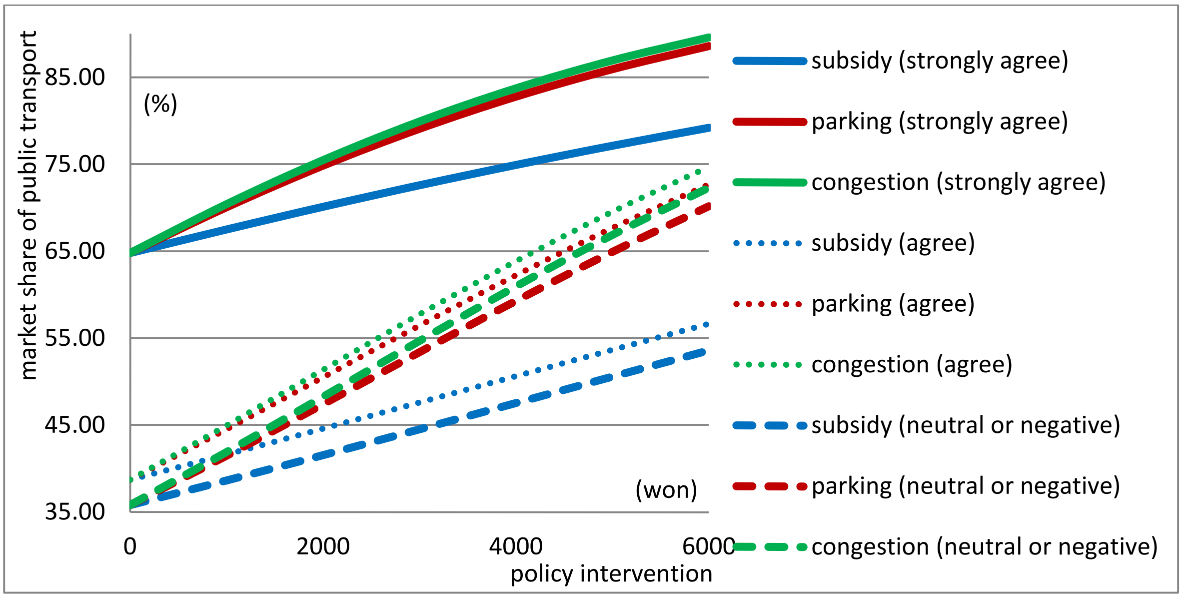
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

If a respondent agrees with the statement that "the use of PT is important in order to reduce global warming and to protect the environment" (moderate positive group), the value of the dummy attribute will be one. In this case, the value of the coefficient (1.0696) is multiplied by the value of the attribute (1) (= 1.0696×1). The utility value of this dummy variable will be 1.0696. Next, if a respondent has a neutral or negative opinion about the statement (negative group), the value of the dummy attribute will be one. In this case, the value of the coefficient (1.1934) is multiplied by the value of the attribute (1) (= 1.1934×1). The utility value of this dummy variable will be 1.1934. Lastly, if a respondent strongly agree with the statement (strong positive group), the value of the dummy attribute will be zero.

Since the signs of the two dummy variables all are positive, the dummy variables will contribute to the increase of utility of car use. All in all, since the magnitude of the coefficient for the negative group is larger than the moderate positive group, it is expected that the negative group tends to prefer the use of a car rather than the moderate positive group. That is, it can be interpreted that people who deny the importance of PT usage for the environment would be more likely to prefer the use of a car.

As can be seen in **Appendix Figure 8-1**, the strong positive group are more likely to use PT rather than the other groups. This result is acceptable and sensible. In particular, the intercept gap between the strong positive group and the moderate positive group is very much wider than the one between the moderate positive group and the negative group.

Appendix Figure 8-1. The market share of PT in the segmented model using dummy variables (Environmental consciousness)



(2) The segmentation method using separate data of the segmented groups

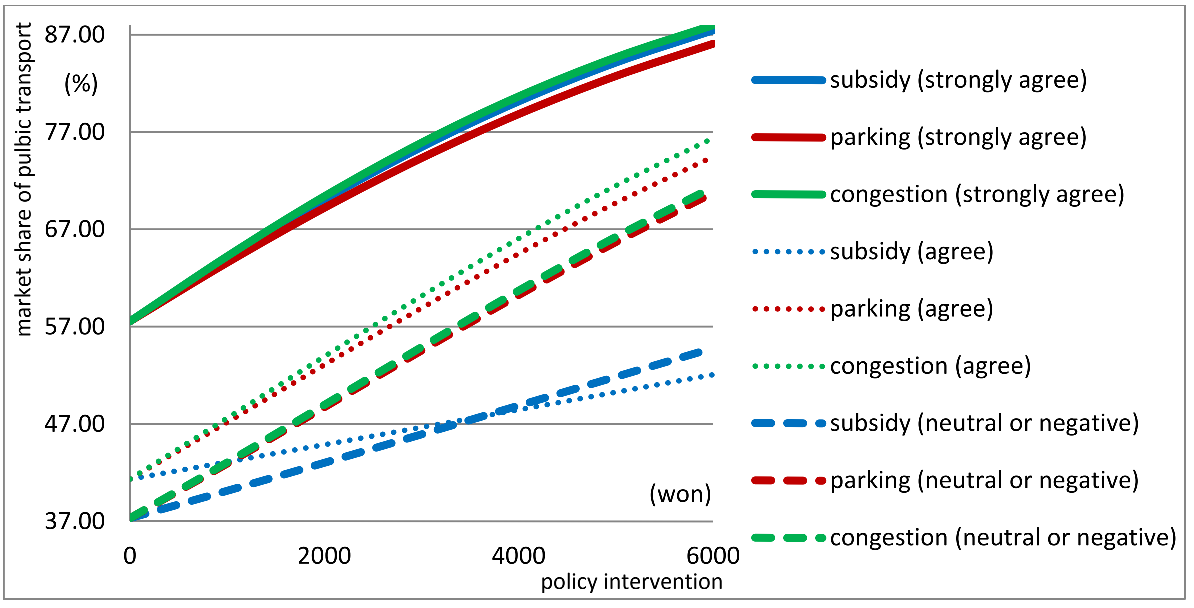
Appendix Table 8-2. The coefficients of segmented models using separated data (Environmental consciousness)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**-0.3050**	**-4.1646****	**0.3497**	**6.3616****	**0.5182**	**5.4183****
PT commuting cost subsidy	β_1	0.2727	**11.8049****	0.0720	**6.3360****	**0.1184**	**5.4399****
Additional parking fee	β_2	-0.2527	**-12.5869****	**-0.2365**	**-17.4462****	**-0.2334**	**-10.2411****
Congestion charge	β_3	**-0.2807**	**-16.0333****	**-0.2539**	**-22.0107****	**-0.2382**	**-12.4051****
L(0)		-4795.885		-5515.372		-1852.782	
L($\widehat{\beta}$)		-2233.816		-4171.539		-1458.702	
ρ^2		0.53422		0.24365		0.21270	
Number of observations		287		353		114	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 8-2**, the sign of the ASC (β_0) for the strong positive group is negative (– 0.3050). It implies that the strong positive group prefers the use of PT rather than the use of a car. Also, all the coefficients (β_1, β_2, and β_3) of MSP for the strong positive group are higher than the other groups. That is, the modal shift effects of MSP for the strong positive group seem to be stronger than the other groups. Therefore, it can be concluded that there is a consistent and strong relationship between environmental consciousness and the modal shift effect of MSP. An interesting point is that modal shift effects of the PT commute cost subsidies for the strong positive group are stronger than those of the additional parking fees.

Appendix Figure 8-2. The market share of PT in the segmented models using separate data (Environmental consciousness)



As can be seen in **Appendix Figure 8-2**, another interesting point is that the modal shift effects of the PT commuting cost subsidies for the moderate positive group are very much lower than those of the negative group.

2. Results of segmentation: Attitude about "the use of PT is helpful for my health."

(1) The segmentation method using dummy variables

In **Appendix Table 8-3**, the ρ^2 of the segmented model (0.351) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with the segmented model is the same as those of the default model. The sign of the ASC (β_0) is negative. The negative ASC means that individuals prefer the use of PT.

Appendix Table 7-3. The coefficients of a segmented model using dummy variables (Health consciousness)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**-0.4556**	**-8.5225****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1250**	**13.1295****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2345**	**-23.5292****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2508**	**-29.4819****
Dummy consciousness of health 1 (strongly agree:0, agree:1)	$\beta_{health1}$			**0.7620**	**14.1139****
Dummy consciousness of health 2 (strongly agree:0, neutral or others:1)	$\beta_{health2}$			**0.7190**	**13.7770****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8045.393	
ρ^2		0.324		0.351	
Number of observations		678		663	

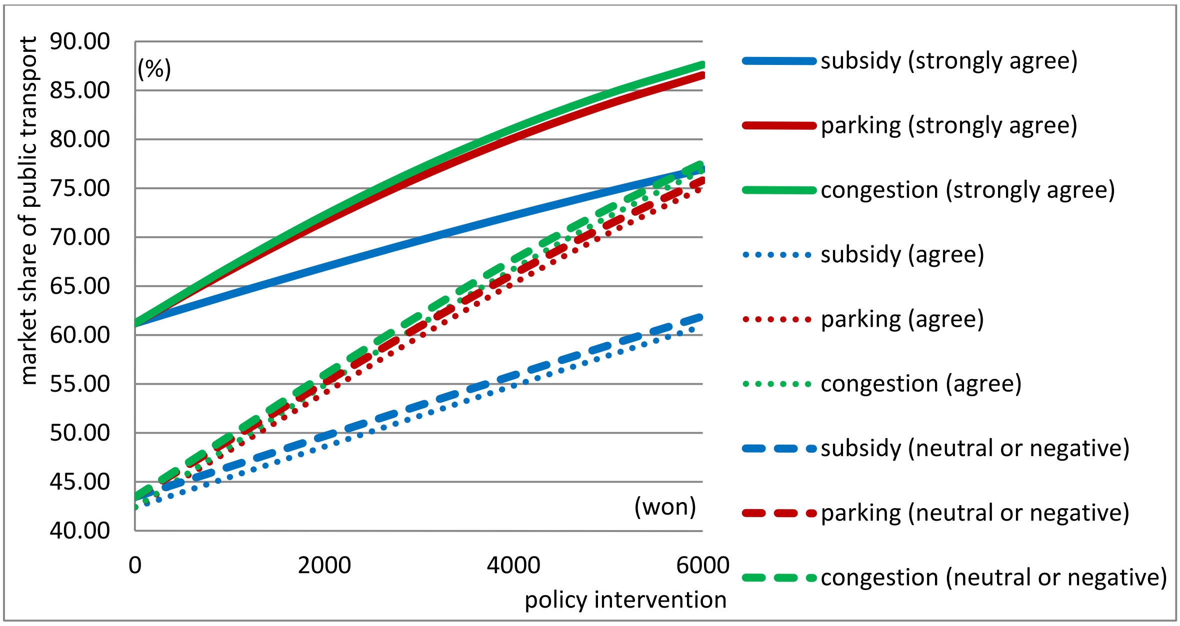
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

If a respondent agrees with the statement that "the use of PT is helpful for my health" (moderate positive group), the value of the dummy attribute will be one. In this case, the value of the coefficient (0.7620) is multiplied by the value of the attribute (1) (= 0.7620×1). The utility value of this dummy variable will be 0.7620. Next, if a respondent has a neutral or negative opinion about the statement (negative group), the value of the dummy attribute will be one. In this case, the value of the coefficient (0.7190) is multiplied by the value of the attribute (1) (= 0.7190×1). The utility value of this dummy variable will be 0.7190. Lastly, if a respondent agrees strongly with the statement (strong positive group), the value of the dummy attribute will be zero.

Also, since the signs of the dummy variables are positive, it is expected that the moderate positive group and the negative group tend to prefer the use of a car. However, the magnitude of coefficients of dummy variables does not have a consistent tendency. In order to achieve consistency, the magnitude of the coefficient for the negative group should be higher than the moderate positive group. This is because under the positive sign, the larger magnitude of the coefficient equates with the higher preference of car use. However, in this case, the magnitude of the coefficient for the negative group

(0.7190) is less than the moderate positive group (0.7620). In conclusion, since there is no consistent tendency, the health consciousness factor has limitations to exactly predict the inclination of dummy variables.

Appendix Figure 8-3. The market share of PT in the segmented model using dummy variables (Health consciousness)



As shown in **Appendix Figure 8-3**, the strong positive group is more likely to use PT rather than the other groups. However, the moderate positive group tends to use PT less than the negative group. This result indicates that there is no consistent trend between the two groups. However, since the gap between the moderate positive group and the negative group is very small, the difference between the two groups can be insignificant. That is, since the difference between the strong positive group and the other two groups is clear, the difference between the moderate positive group and the negative group can be ignored in the interpretation.

(2) The segmentation method using separate data of the segmented groups

In **Appendix Table 8-4**, the sign of the ASC (β_0) for the strong positive group is negative. It implies that the strong positive group prefers to the use of PT rather than the use of a car. Also, the value of the coefficient β_1 (0.0371) for the moderate positive group is lower than the negative group (0.1810) and the strong positive group (0.2184). It implies that that modal shift effect of the PT commuting cost subsidies for the moderate positive group seems to be much weaker than the other groups. In particular, the value of the coefficient β_1 of the strong positive group is higher than that of the coefficient β_2. It implies that the modal shift effects of the PT commuting cost subsidies for the strong positive group are stronger than those of additional parking fees.

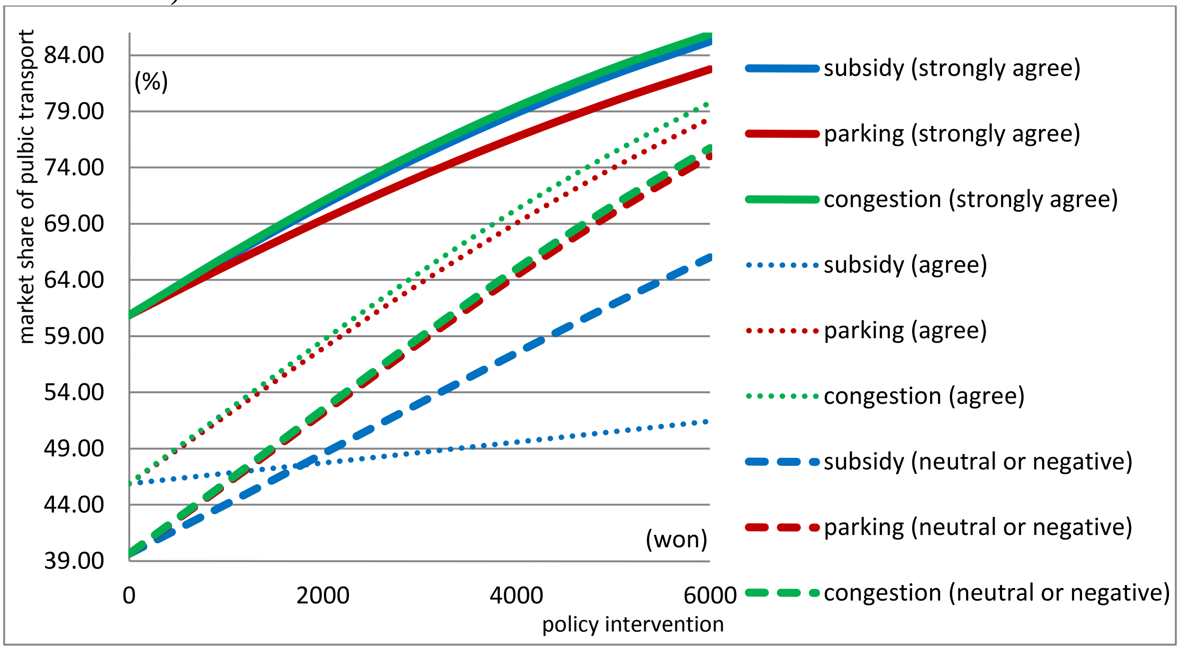
Appendix Table 8-4. The coefficients of segmented models using separate data (Health consciousness)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**-0.4415**	**-5.3560****	**0.1653**	**2.5457***	**0.4214**	**6.7485****
PT commuting cost subsidy	β_1	**0.2184**	**9.4196****	**0.0371**	**3.0079****	**0.1810**	**11.4401****
Additional parking fee	β_2	**-0.1877**	**-8.7461****	**-0.2421**	**-14.5537****	**-0.2536**	**-16.5025****
Congestion charge	β_3	**-0.2269**	**-12.2563****	**-0.2565**	**-18.0937****	**-0.2599**	**-19.9025****
L(0)		-3474.054		-3880.931		-4771.625	
$L(\widehat{\beta})$		-1832.714		-2820.383		-3351.569	
ρ^2		0.47246		0.27327		0.29760	
Number of observations		211		248		293	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

As indicated in **Appendix Figure 8-4**, modal shift effects of the PT commuting cost subsidies for the moderate positive group, which acknowledges the usefulness of PT use for their healthy improvement, are very much lower than the other groups. Another interesting point is that the modal shift effects of the PT commute cost subsidies for the strong positive group are stronger than those of additional parking fees.

Appendix Figure 8-4. The market share of PT in the segmented models using separate data (Health consciousness)



3. Results of segmentation: Attitude about "the freedom of choosing transport modes should not be restricted by government regulation."

(1) The segmentation method using dummy variables

In **Appendix Table 8-5**, the ρ^2 of the segmented model (0.346) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with the segmented model are the same as those of the default model. The sign of the ASC ($\beta_{0,}$ 0.2638) is positive. The positive ASC means that individuals prefer the use of the car.

Appendix Table 8-5. The coefficients of a segmented model using dummy variables (Freedom consciousness)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**0.2638**	**5.1092****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1234**	**13.2503****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2336**	**-23.5541****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2507**	**-29.6163****
Dummy consciousness of freedom 1 (strongly agree:0, agree:1)	β_{freee1}			0.0668	1.3976
Dummy consciousness of freedom 2 (strongly agree:0, neutral or others:1)	β_{freee2}			**-0.5746**	**-10.9128****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8133.399	
ρ^2		0.324		0.346	
Number of observations		678		663	

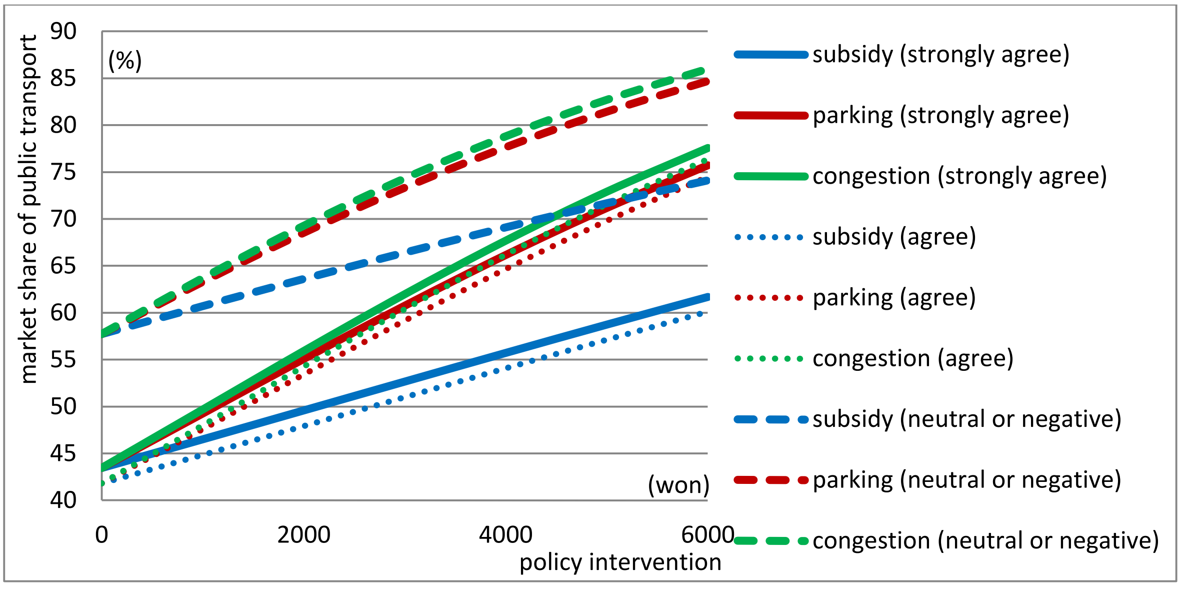
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

If a respondent agrees with the statement that "the freedom of choosing transport modes should not be restricted by government regulation" (moderate positive group), the value of the dummy attribute will be one. In this case, the value of the coefficient (0.0668) is multiplied by the value of the attribute (1) (= 0.0668×1). The utility value of this dummy variable will be 0.0668. Next, if a respondent has a neutral or negative opinion about the statement (negative group), the value of the dummy attribute will be one. In this case, the value of the coefficient (– 0.5746) is multiplied by the value of the attribute (1) (= – 0.5746×1). The value of this dummy variable will be – 0.5746. Lastly, if a respondent agrees strongly with the statement (strong positive group), the value of the dummy attribute will be zero.

However, the coefficient of Dummy variable 1 (β_{free1}) shows statistically insignificance since the absolute t-value (1.3976) is less than 1.65. It means that there are no statistically significant differences between the strong positive group and the moderate positive group. Therefore, only the coefficient of Dummy variable 2 (β_{free2}) should be treated as an appropriate dummy variable.

Therefore, in the interpretation of dummy variables, this statistically insignificant dummy variable (β_{free1}) should be excluded.

Appendix Figure 8-5. The market share of PT in the segmented model using dummy variables (Freedom consciousness)



As shown in **Appendix Figure 8-5**, the strong positive group is more likely to use the car rather than the other groups. That is, people who deny the necessity of governmental regulation tend to use private vehicles. In **Appendix Figure 8-5**, the moderate positive group is not placed between the negative group and the strong positive group. However, since the modal shift probability curves of the moderate positive group are statistically insignificant, the interpretation is not needed.

(2) The segmentation method using separate data of the segmented groups

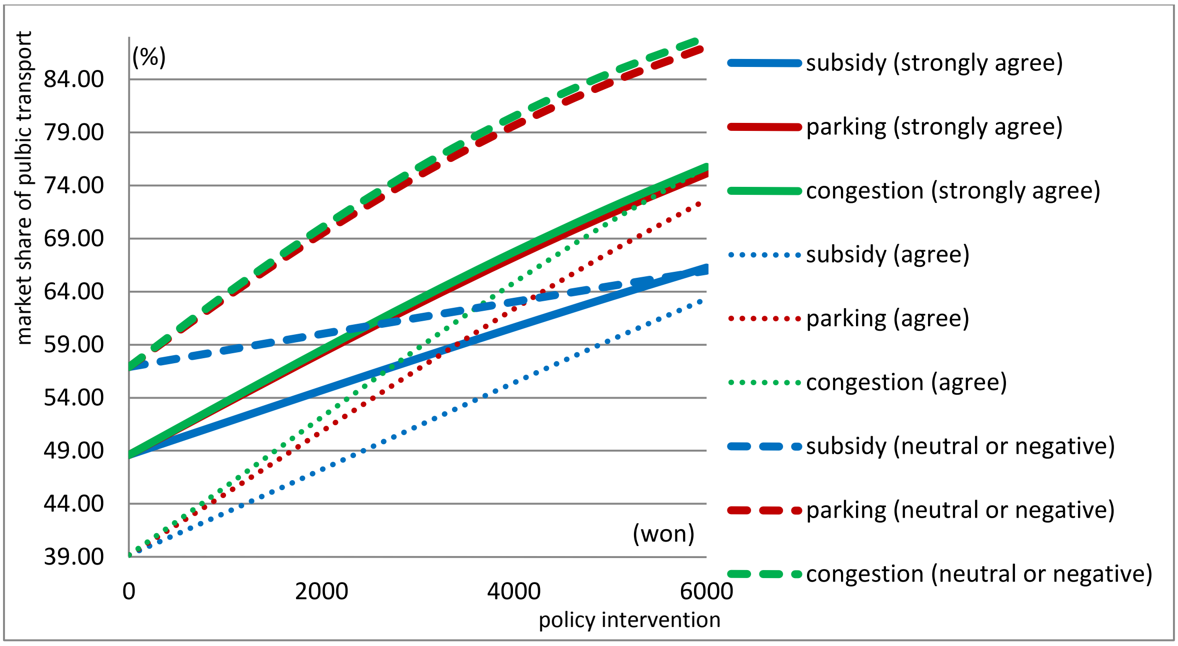
Appendix Table 8-6. The coefficients of segmented models using separated data (Freedom consciousness)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	0.0556	0.7329	**0.4406**	**7.1608****	**-0.2775**	**-3.9867****
PT commuting cost subsidy	β_1	**0.1219**	**7.2758****	**0.1645**	**11.0815****	0.0640	**3.9005****
Additional parking fee	β_2	**-0.1934**	**-10.4033****	**-0.2363**	**-15.8296****	**-0.2717**	**-14.2214****
Congestion charge	β_3	**-0.1993**	**-12.6924****	**-0.2632**	**-20.6367****	**-0.2851**	**-17.2729****
L(0)		-3026.281		-4839.554		-4260.776	
$L(\widehat{\beta})$		-2212.584		-3486.743		-2392.389	
ρ^2		0.26888		0.27953		0.43851	
Number of observations		198		298		255	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 8-6**, the sign of the ASC (β_0) for the negative group (– 0.2775) is negative. It implies that the negative group prefers to the use of PT rather than the use of a car. That is, the negative group, which acknowledges the necessity of governmental regulation, prefers PT use. In addition, the value of the coefficient (β_1) of the PT commuting cost subsidies (0.0640) for the negative group is lower than that of the strong positive group (0.1219) and the moderate positive group (0.1645). It means that the modal shift effects of PT commuting cost subsidies for people who acknowledge the necessity of governmental regulation are markedly weaker than the other people.

Appendix Figure 8-6. The market share of PT in the segmented models using separate data (Freedom consciousness)



As can be seen in **Appendix Figure 8-6**, the modal shift effects of the PT commuting cost subsidies for the negative group, which acknowledges the necessity of governmental regulation, are remarkably lower than that of the other groups. In addition, the modal shift effects of congestion charges and additional parking fees for the negative group and the moderate positive group are stronger than the strong positive group.

As can be seen in **Appendix Figure 8-6**, the moderate positive group is not placed between the negative group and the strong positive group. Therefore, it can be concluded that there is no consistent tendency of the attitude about the necessity of governmental regulation and the choice of travel mode.

4. Results of segmentation: Attitude about "convenience is a very important factor in determining commuting."

(1) The segmentation method using dummy variables

Appendix Table 8-7. The coefficients of a segmented model using dummy variables (Convenience importance)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**0.2303**	**5.2178****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1221**	**13.2580****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2321**	**-23.5447****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2484**	**-29.5329****
Dummy importance of convenience 1 (strongly agree:0, agree:1)	$\beta_{conven1}$			**-0.0921**	**-2.2761***
Dummy importance of convenience 2 (strongly agree:0, neutral or others:1)	$\beta_{conven2}$			**-1.1003**	**-13.7828****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8201.716	
ρ^2		0.324		0.339	
Number of observations		678		672	

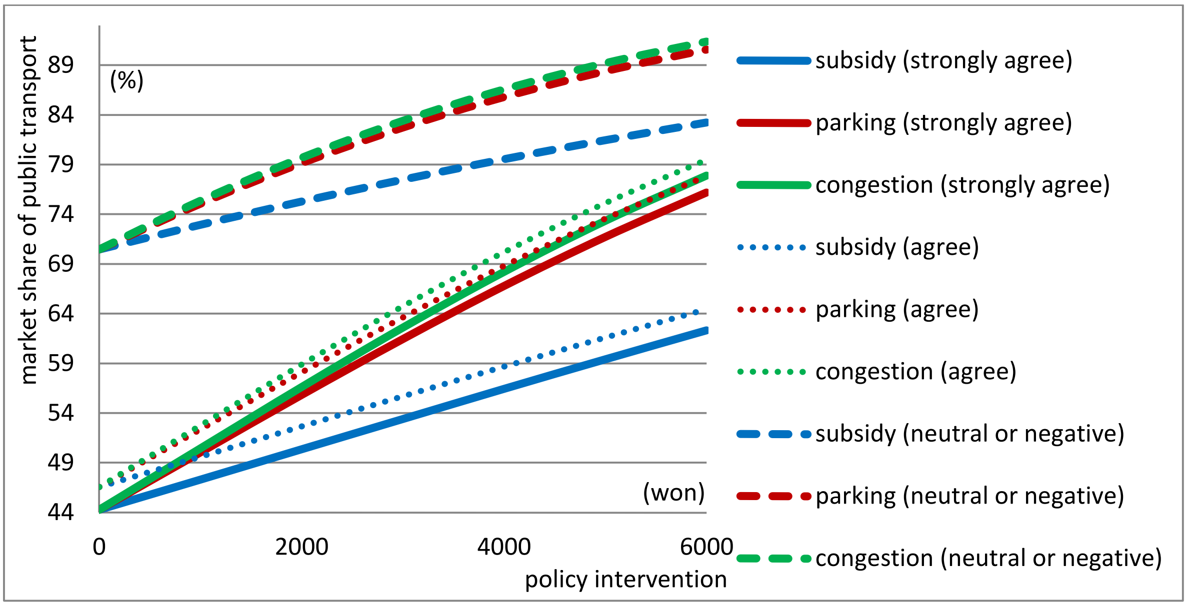
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

In **Appendix Table 8-7**, the ρ^2 of the segmented model (0.339) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with the segmented model are the same as those of the default model. The sign of the ASC (β_0, 0.2303) is positive. The positive ASC means that individuals prefer the use of a car.

If a respondent agrees with the statement that "convenience is a very important factor in determining commuting" (moderate positive group), the value of the dummy attribute will be one. In this case, the value of the coefficient (– 0.0921) is multiplied by the value of the attribute (1) (= – 0.0921×1). The utility value of this dummy variable will be – 0.0921. Next, if a respondent has a neutral or negative opinion about that statement (negative group), the value of the dummy attribute will be one. In this case, the value of the coefficient (– 1.1003) is multiplied by the value of the attribute (1) (= – 1.1003×1). The utility value of this dummy variable will be – 1.1003. Lastly, if a respondent agrees strongly with that statement (strong positive group), the value of the dummy attribute will be zero.

In addition, since the signs of the two dummy variables are negative, the dummy variables will contribute to the increase of utility of car use. All in all, since the magnitude of the coefficient for the negative group is larger than the moderate positive group, it is expected that the negative group tends to prefer the use of PT. That is, people who deny the importance of convenience would be more likely to prefer the use of PT.

Appendix Figure 8-7. The market share of PT in the segmented model using dummy variables (Convenience importance)



As can be seen in **Appendix Figure 8-7**, the negative group is most likely to use PT rather than the strong positive group and the moderate positive group. That is, people who deny the importance of convenience tend to prefer the use of PT.

(2) The segmentation method using separate data of the segmented groups

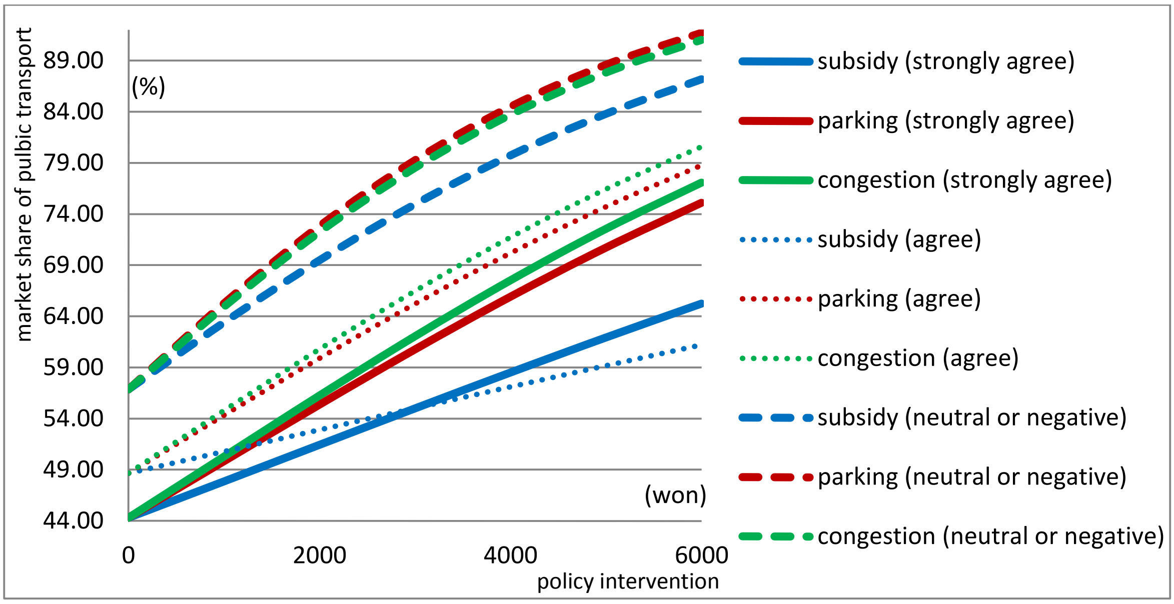
Appendix Table 8-8. The coefficients of segmented models using separated data (Convenience importance)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**0.2285**	**4.0940****	0.0537	0.9049	-0.2757	-1.9483
PT commuting cost subsidy	β_1	**0.1431**	**10.9118****	0.0850	**6.5118****	**0.2733**	**5.6230****
Additional parking fee	β_2	**-0.2220**	**-16.1522****	**-0.2274**	**-15.0994****	-0.3551	**-8.3835****
Congestion charge	β_3	**-0.2400**	**-20.5092****	**-0.2462**	**-19.1564****	-0.3402	**-9.2981****
L(0)		-5807.187		-5040.566		-1446.598	
$L(\widehat{\beta})$		-4124.33		-3485.482		-574.1352	
ρ^2		0.2897886		0.3085138		0.6031136	
Number of observations		368		314		79	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 8-8**, all the coefficients (β_1, β_2 and β_3) of the MSP for the negative group are higher than the other groups. That is, the modal shift effects of the MSP for the negative group, which denies the importance of convenience, are stronger than the other groups. In short, people who deny the importance of convenience would more likely to prefer the use of PT. In addition, a remarkable point is that the absolute value (– 0.3551) of the coefficient for additional parking fees (β_2) with the negative group is greater than that (– 0.3402) of the congestion charges (β_3).

Appendix Figure 8-8. The market share of PT in the segmented models using separate data (Convenience importance)



As can be seen in **Appendix Figure 8-8**, the modal shift effects of the PT commuting cost subsidies for the moderate positive group are remarkably lower than those of the other groups.

5. Results of segmentation: Attitude about "time is a very important factor in determining commuting."

(1) The segmentation method using dummy variables

Appendix Table 8-9. The coefficients of a segmented model using dummy variables (Time importance)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	-0.0235	-0.5300
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1198**	**12.9648****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2323**	**-23.6005****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2482**	**-29.5580****
Dummy importance of time 1 (strongly agree:0, agree:1)	β_{time1}			**0.1956**	**4.7779****
Dummy importance of time 2 (strongly agree:0, neutral or others:1)	β_{time2}			**0.2733**	**4.0172****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8201.716	
ρ^2		0.324		0.339	
Number of observations		678		667	

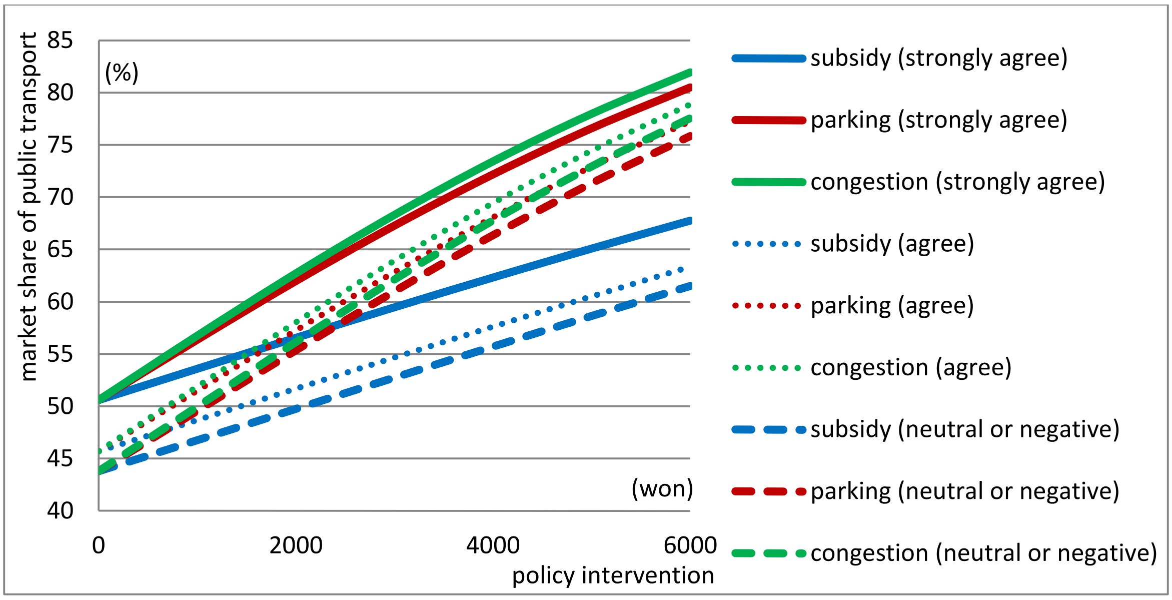
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 8-9**, the ρ^2 of the segmented model (0.339) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with the segmented model are the same as those of the default model.

If a respondent agrees with the statement that "time is a very important factor in determining commuting" (moderate positive group), the value of the dummy attribute will be one. In this case, the value of the coefficient (0.1956) is multiplied by the value of the attribute (1) (= 0.1956×1). The utility value of this dummy variable will be 0.1956. Next, if a respondent has a neutral or negative opinion about the statement (negative group), the value of the dummy attribute will be one. In this case, the value of the coefficient (0.2733) is multiplied by the value of the attribute (1) (= 0.2733×1). The utility value of this dummy variable will be 0.2733. Lastly, if a respondent agrees strongly with the statement (strong positive group), the value of the dummy attribute will be zero.

In addition, since the signs of the dummy variables are positive, the dummy variables will contribute to the increase of the utility of car use. All in all, since the magnitude of the coefficient for the negative group is larger than the moderate positive group, it is expected that the negative group tends to prefer the use of a car. That is, people who deny the importance of time would be more likely to prefer the use of a car. Thus, people who accept the importance of time tend to use PT. While the average one-way commuting time of car users is 46 minutes 24 seconds, the average one-way commuting time of PT users is 60 minutes 25 seconds. That is, in terms of the average commuting time, the use of PT takes a long time compared to the use of the car. Therefore, it can be interpreted that many people may give priority to the benefits of the punctuality gained from the use of PT rather than the benefits of reduced time values obtained by the use of the car.

Appendix Figure 8-9. The market share of PT in the segmented model using dummy variables (Time importance)



As can be seen in **Appendix Figure 8-9**, the strong positive group is most likely to use PT rather than the other groups. It indicates that people who acknowledge the obvious importance of time tend to use PT rather than a car.

(2) The segmentation method using separate data of the segmented groups

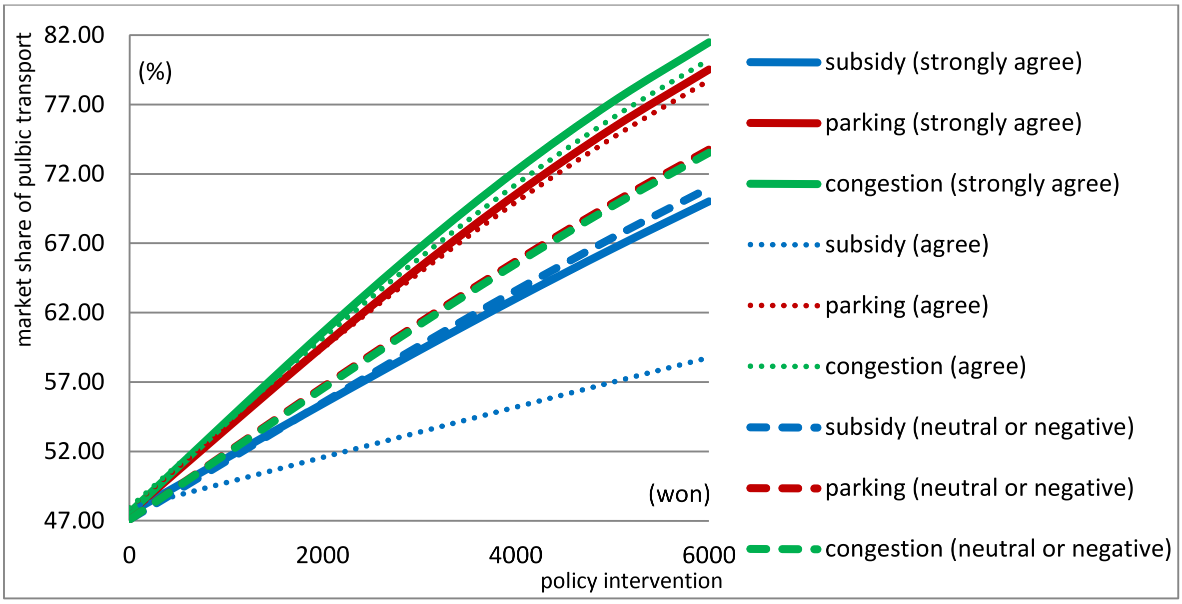
Appendix Table 8-10. The coefficients of segmented models using separated data (Time importance)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	0.0979	1.6898	0.0830	1.4351	0.1174	0.9317
PT commuting cost subsidy	β_1	**0.1577**	**11.1044****	0.0729	**5.6280****	**0.1687**	**5.5242****
Additional parking fee	β_2	**-0.2425**	**-16.3518****	**-0.2320**	**-15.8793****	**-0.1918**	**-6.2864****
Congestion charge	β_3	**-0.2633**	**-20.6910****	**-0.2474**	**-19.8629****	**-0.1899**	**-7.4187****
L(0)		-5827.981		-5247.817		-1127.75	
$L(\widehat{\beta})$		-3706.867		-3688.261		-824.8875	
ρ^2		0.36395		0.29718		0.26856	
Number of observations		355		331		70	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 8-10**, the value of the coefficient (β_1) of the PT commuting cost subsidies (0.0729) for the moderate positive group is lower than the strong positive group (0.1577) and the negative group (0.1689). In addition, the absolute value of the coefficient (β_2) for additional parking fees (– 0.1918) with the negative group are greater than that (– 0.1899) of the congestion charges (β_3). It suggests that the modal shift effects of additional parking fees for the negative group seem to be stronger than congestion charges.

Appendix Figure 8-10. The market share of PT in the segmented models using separate data (Time importance)



As shown in **Appendix Figure 8-10**, the modal shift effects of PT commuting cost subsidies for the moderate positive group are remarkably lower than that of the other groups.

As can be seen in **Appendix Figure 8-10**, the moderate positive group is not placed between the negative group and the strong positive group. Therefore, in the segmentation models using separate data of the segmented groups, there seems to be no consistent tendency between the attitude about the importance of time and the choice of travel mode.

6. Results of segmentation: Attitude about "cost is a very important factor in determining commuting."

(1) The segmentation method using dummy variables

Appendix Table 8-11. The coefficients of a segmented model using dummy variables (Cost importance)

Coefficient		Model B0		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3340**	**6.6690****	**-0.6170**	**-10.6978****
PT commuting cost subsidy	β_1	**0.2020**	**12.6600****	**0.1262**	**13.3115****
Additional parking fee	β_2	**-0.3120**	**-19.5860****	**-0.2450**	**-24.1295****
Congestion charge	β_3	**-0.3250**	**-23.3930****	**-0.2623**	**-30.2192****
Dummy importance of cost 1 (strongly agree:0, agree:1)	β_{cost1}			**0.6152**	**10.8394****
Dummy importance of cost 2 (strongly agree:0, neutral or others:1)	β_{cost2}			**1.4729**	**25.0776****
L(0)		-12405.26		-12405.26	
L($\widehat{\beta}$)		-8389.1		-8201.716	
ρ^2		0.324		0.339	
Number of observations		678		666	

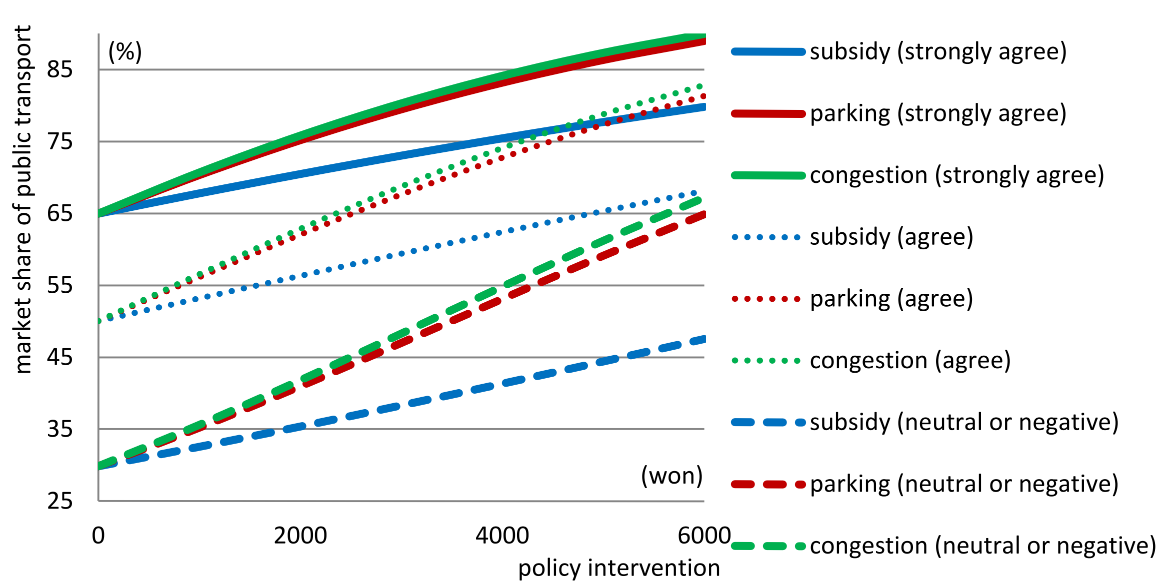
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 8-11**, the ρ^2 of the segmented model (0.339) is higher than that of the default model (0.324). In addition, the signs and the orders of the magnitude of the coefficients of the MSP with the segmented model are the same as those of the default model B0. The sign of the ASC (β_0, –0.6170) is negative. The negative ASC means that individuals prefer the use of PT.

If a respondent agrees with the statement that "cost is a very important factor in determining commuting" (moderate positive group), the value of the dummy attribute will be one. In this case, the value of the coefficient (0.6152) is multiplied by the value of the attribute (1) (= 0.6152×1). The utility value of this dummy variable will be 0.6152. Next, if a respondent has a neutral or negative opinion about that statement (negative group), the value of the dummy attribute will be one. In this case, the value of the coefficient (1.4729) is multiplied by the value of the attribute (1) (= 1.4729×1). The utility value of this dummy variable will be 1.4729. Lastly, if a respondent agrees strongly with that statement (strong positive group), the value of the dummy attribute will be zero.

In addition, since the signs of the two dummy variables are positive, these dummy variables will contribute to the increase in the utility of car use. All in all, since the magnitude of the coefficient for the negative group is larger than the moderate positive group, it is expected that the negative group, which denies the importance of cost, tends to prefer the use of the car rather than the use of PT.

Appendix Figure 8-11. The market share of PT in the segmented model of using dummy variables (Cost importance)



As can be seen in **Appendix Figure 8-11**, considering the position of the intercept of each group, the strong positive group, which acknowledges the importance of cost, is more likely to use PT rather than the other groups.

(2) The segmentation method using separate data of the segmented groups

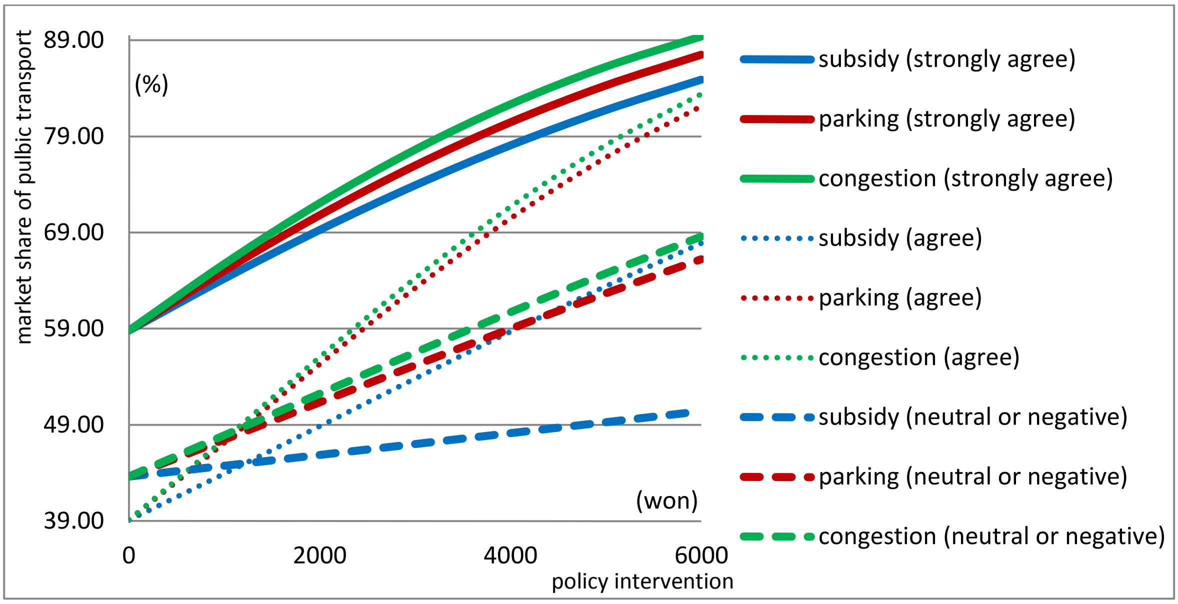
Appendix Table 8-12. The coefficients of segmented models using separated data (Cost importance)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**-0.3555**	**-3.8815****	**0.4429**	**7.2465****	**0.2559**	**3.9205****
PT commuting cost subsidy	β_1	**0.2284**	**8.2105****	**0.1986**	**12.2587****	**0.0453**	**3.8344****
Additional parking fee	β_2	**-0.2651**	**-10.4197****	**-0.3280**	**-20.3345****	**-0.1549**	**-10.0164****
Congestion charge	β_3	**-0.2957**	**-13.2392****	**-0.3429**	**-24.4551****	**-0.1727**	**-13.2821****
L(0)		-3091.436		-5683.807		-3409.591	
$L(\widehat{\beta})$		-1413.577		-3342.285		-2975.082	
ρ^2		0.54274		0.41196		0.12744	
Number of observations		181		356		218	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

In **Appendix Table 8-12**, the sign of the ASC (β_0) for the strong positive group is negative. It implies that the strong positive group, who acknowledge the importance of cost, prefers to the use of PT rather than the use of the car. In addition, since all the coefficients (β_1, β_2 and β_3) of the strong positive group are higher than those of the other group, it can be inferred that the modal shift effects of the MSP for the strong positive group are higher than the other groups.

Appendix Figure 8-12. The market share of PT in the segmented models of using separate data (Cost importance)



As can be seen in **Appendix Figure 8-12**, the modal shift effects of the PT commuting cost subsidies for the negative group, which denies the importance of cost, are remarkably lower than those of the other groups. In addition, the modal shift effects of congestion charges and additional parking fees for the moderate positive group are very much stronger than the other groups.

As can be seen in **Appendix Figure 8-12**, the moderate positive group is not placed between the negative group and the strong positive group. Therefore, it can be concluded that there is no consistent tendency of the attitude about the importance of cost and the choice of travel mode.

<Reference Data 2>

(1) Segmentation results of the segmented model B2 using attitudinal dummy variables

The results of segmentation analysis in the segmented model B2, a model with interaction terms comprising only statistically significant coefficients, using dummy variables are almost the same as those of the segmented model B0. That is, the position of the intercept for each segmented group in the segmented model B2 is almost the same as that of the segmented model B0. In addition, the sensitivity to the level of the MSP across each group in the segmented model B2 is also almost the same as that of the segmented model B0. In other words, although there are small differences between the segmented model B2 and segmented model B0 in the light of the magnitude of the modal shift effect of the MSP, the order of modal shift effect of the MSP shows almost the same result.

In comparison of the value of ρ^2 in **Reference Table 3-1** and **Table 7-12 (page 163)**, the segmented model B2 (0.336) is higher than the semented model B0 (0.334). It means that the validity of the segmented model with interaction terms is higher than that of the segmented model without interaction terms.

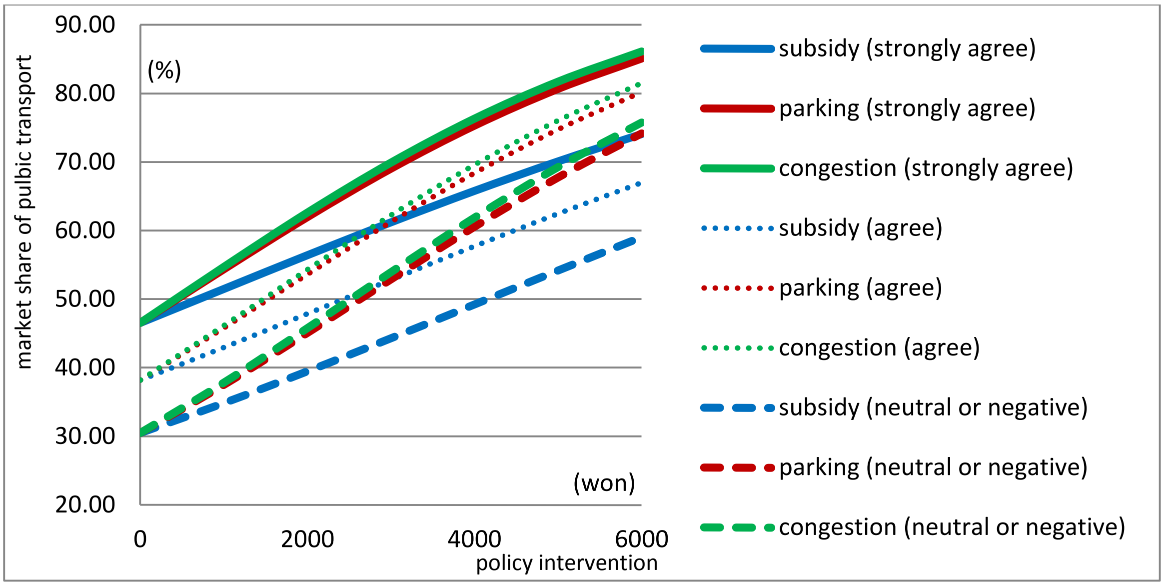
Reference Table 3-1. The coefficients of a segmented model B2 using dummy variables (Congestion consciousness) (compare **Table 7-12, page 163**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.1397**	**2.6168****
P commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.1983**	**12.2886****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3134**	**-19.4679****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3273**	**-23.2952****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0179**	**3.9753****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0189**	**5.0010****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0213**	**5.0558****
Dummy consciousness of congestion severity1 (strongly agree:0, agree:1)	$\beta_{congestion\ 1}$			**0.3427**	**8.1027****
Dummy consciousness of congestion severity2 (strongly agree:0,neutral or others:1)	$\beta_{congestion\ 2}$			**0.6851**	**11.0618****
L(0)		12405.26		-12405.26	
L($\widehat{\beta}$)		8354.584		-8230.935	
ρ^2		0.327		0.336	
Number of observations		678		674	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

For example, as shown in **Reference Figure 3-1**, the position of the intercept for people who agree strongly with the statement that ‘congestion problems are very severe during the morning peak’ is higher than that of the other group people. Like this, as shown in **Figure 7-4 (page 164)**, the position of the intercept of people who agree strongly with that statement is higher than that of the other group people. As a result, the position of the intercept of both is similar to each other. Also, the order of the modal shift effect of each MSP in **Reference Figure 3-1** is similar to that of **Figure 7-4 (page 164)**. All in all, the results of segmentation analyses for all the attitudinal groups in the segmented model B2 are similar to those of the segmented model B0 in terms of the position of the intercept as well as the modal shift effect of the MSP.

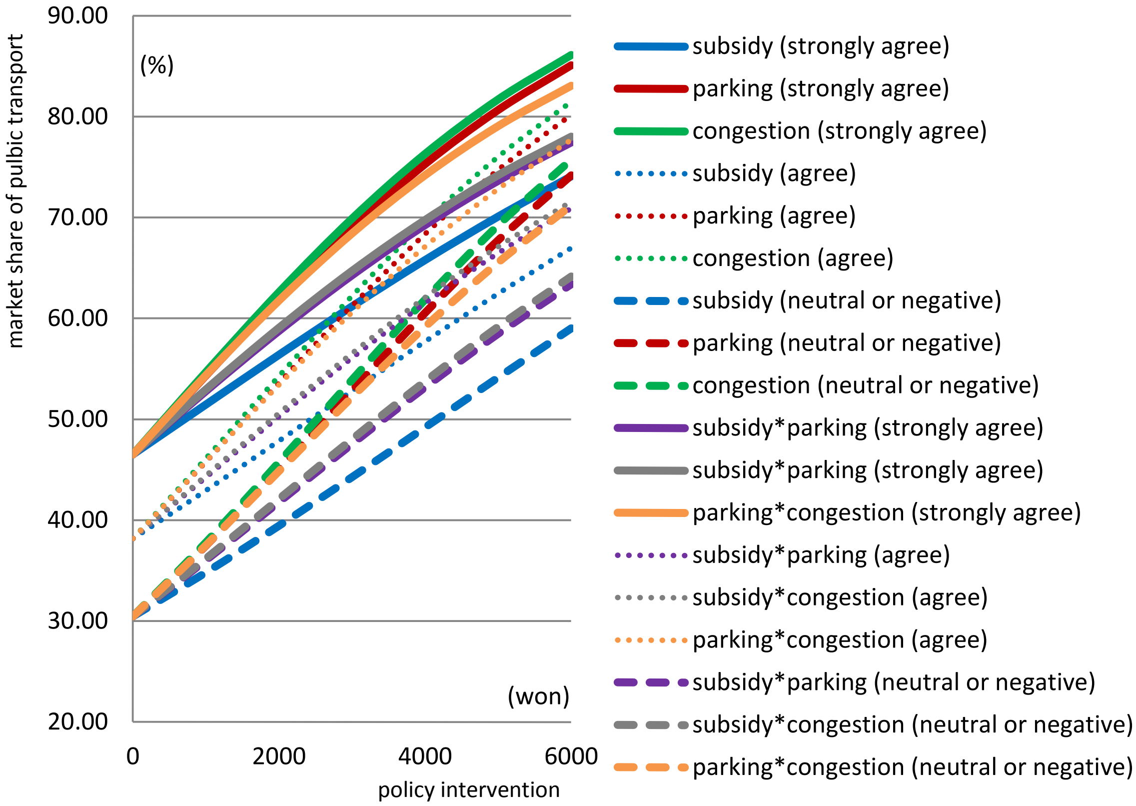
Reference Figure 3-1. The market share of PT in the segmented model B2 of using dummy variables (Congestion consciousness) (compare **Figure 7-4, page 164**)



Meanwhile, the market share value of PT for the combination (see the orange straight line) of additional parking fees (see the red straight line) and congestion charges (see the green straight line) in **Reference Figure 3-2** is similar to that of **Figure 6-16** (see model B2, ‘parking + congestion’ graphs, **page 140**). In addition, the graphs of other combinations in **Reference Figure 3-2** are similar to those of **Figure 6-16 (page 140)**.

Since the results of segmentation analysis for other attitudinal segmented factors concerning the combined MSPs are similar to those of ‘the consciousness about congestion severity’ factor, the description is omitted.

Reference Figure 3-2. The market share of PT in the segmented model B2 of using dummy variables with combined MSP curves (Congestion consciousness)



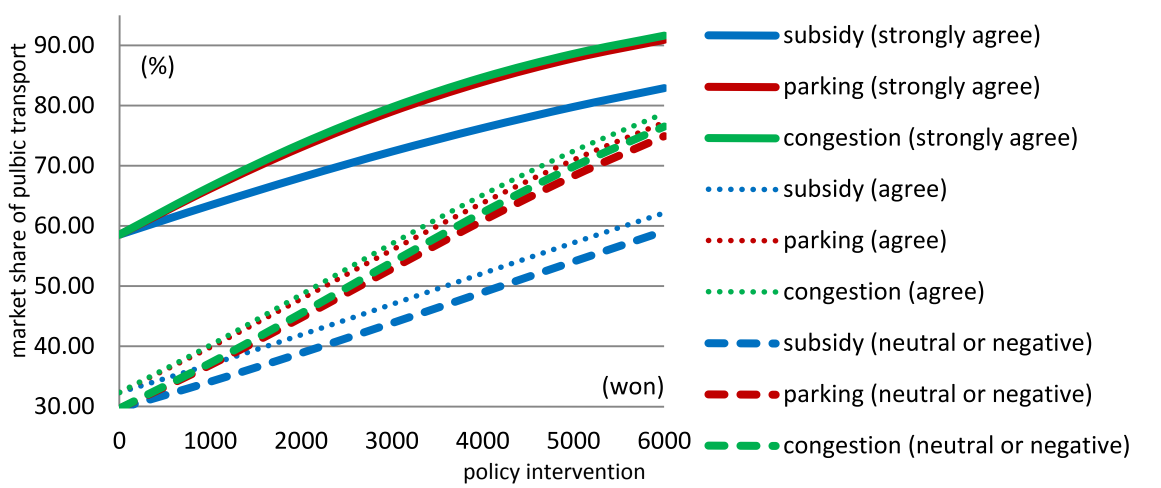
Reference Table 3-2. The coefficients of a segmented model B2 using dummy variables (Environmental consciousness) (see **Appendix Table 8-1, page 391**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**-0.3454**	**-5.8644****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2056**	**12.4905****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3265**	**-19.7792****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3410**	**-23.6867****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0184**	**4.0401****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0198**	**5.1758****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0226**	**5.2445****
Dummy consciousness of environment 1 (strongly agree:0, agree:1)	β_{env1}			**1.0840**	**22.8069****
Dummy consciousness of environment 2 (strongly agree:0, neutral or others:1)	β_{env2}			**1.2101**	**20.1251****
L(0)		12405.26		-12405.26	
L($\widehat{\beta}$)		8354.584		-7864.06	
ρ^2		0.327		0.366	
Number of observations		678		665	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 3-3. The market share of PT in the segmented model B2 of using dummy variables (Environmental consciousness) (see **Appendix Figure 8-1, page 392**)



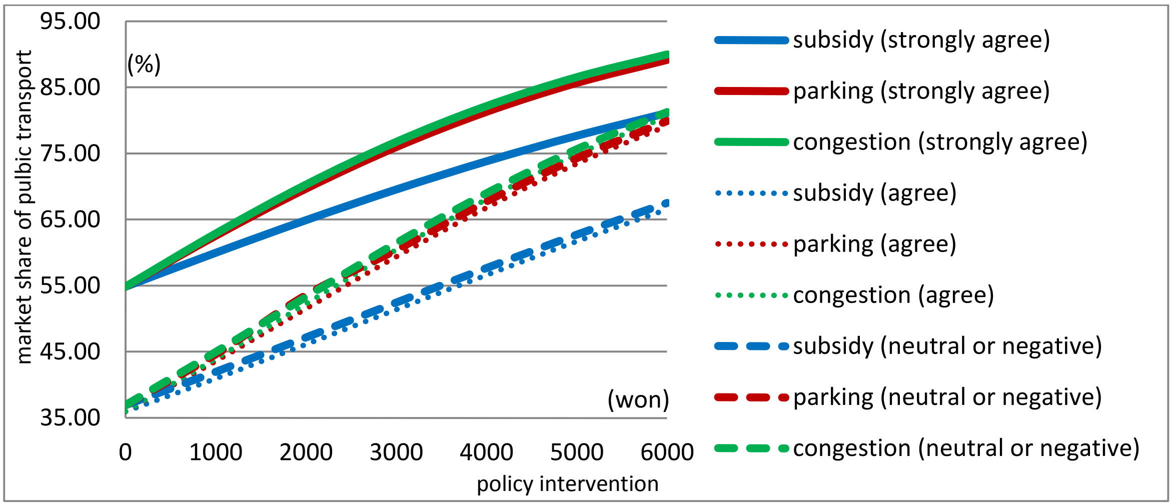
Reference Table 3-3. The coefficients of a segmented B2 using dummy variables (Health consciousness) (see **Appendix Table 8-3, page 394**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**-0.1924**	**-3.0931****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2110**	**12.7006****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3193**	**-19.5745****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3339**	**-23.4483****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0185**	**4.0165****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0204**	**5.2786****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0222**	**5.1928****
Dummy consciousness of health 1 (strongly agree:0, agree:1)	$\beta_{health1}$			**0.7715**	**14.1905****
Dummy consciousness of health 2 (strongly agree:0, neutral or others:1)	$\beta_{health2}$			**0.7284**	**13.8567****
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-8010.935	
ρ^2		0.327		0.354	
Number of observations		678		663	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 3-4. The market share of PT in the segmented model B2 of using dummy variables (Health consciousness) (see **Appendix Figure 8-3, page 395**)



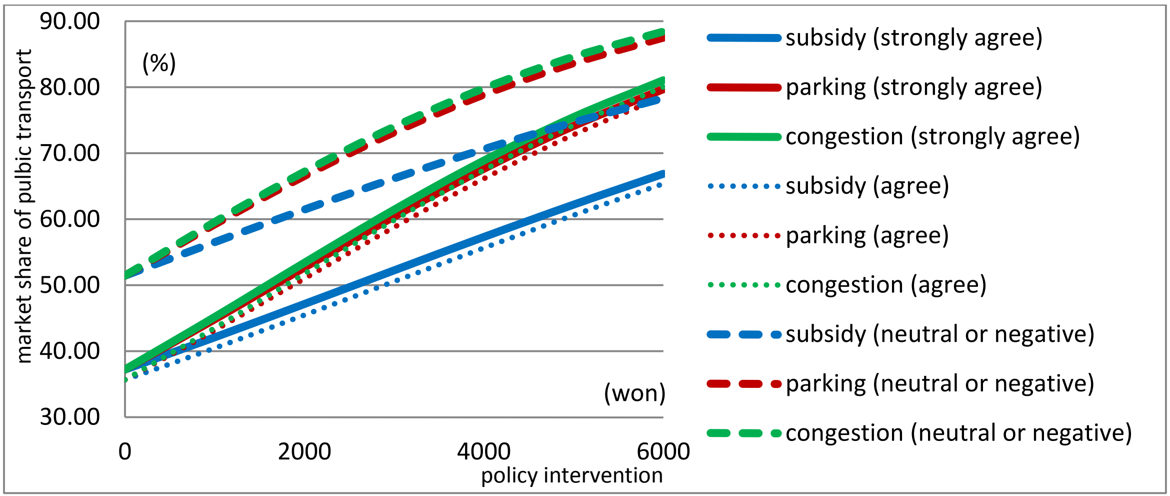
Reference Table 3-4. The coefficients of a segmented model B2 using dummy variables (Freedom consciousness) (see **Appendix Table 8-5, page 397**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.5244**	**8.5345****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2047**	**12.5388****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3152**	**-19.3833****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3299**	**-23.2332****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0179**	**3.9349****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0192**	**5.0120****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0211**	**4.9669****
Dummy consciousness of freedom 1 (strongly agree:0, agree:1)	β_{freee1}			0.0677	1.4101
Dummy consciousness of freedom 2 (strongly agree:0, neutral or others:1)	β_{freee2}			**-0.5819**	**-10.9806****
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-8081.447	
ρ^2		0.327		0.349	
Number of observations		678		663	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 3-5. The market share of PT in the segmented model B2 of using dummy variables (Freedom consciousness) (see **Appendix Figure 8-5, page 398**)

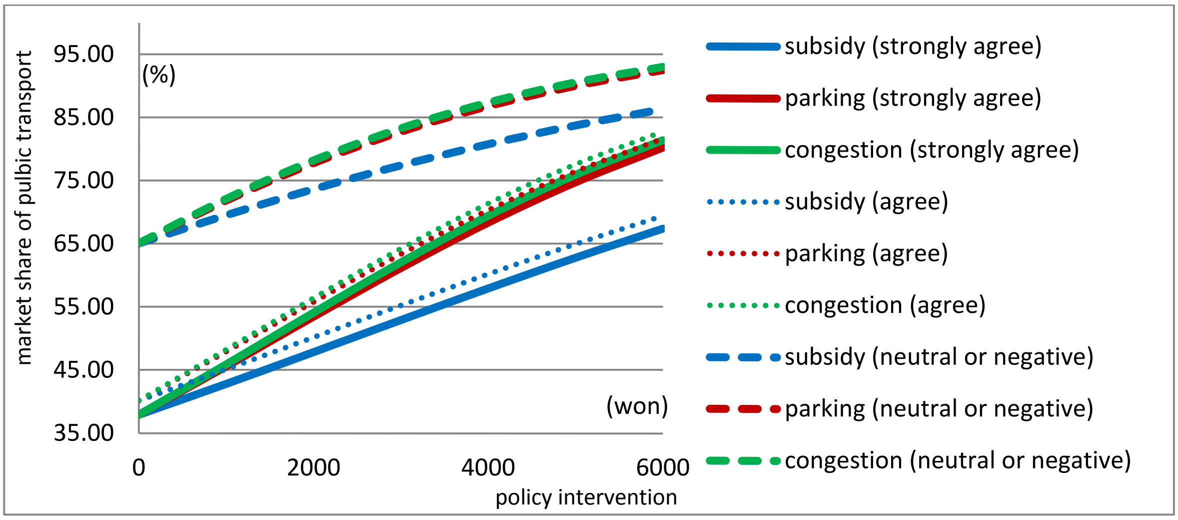


Reference Table 3-5. The coefficients of a segmented model B2 using dummy variables (Convenience importance) (see **Appendix Table 8-7, page 400**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.4936**	**8.9636****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2032**	**12.6083****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3155**	**-19.5250****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3282**	**-23.2911****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0180**	**4.0115****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0189**	**5.0000****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0217**	**5.1306****
Dummy importance of convenience 1 (strongly agree:0, agree:1)	$\beta_{conven1}$			**-0.0937**	**-2.3023***
Dummy importance of convenience 2 (strongly agree:0, neutral or others:1)	$\beta_{conven2}$			**-1.1142**	**-13.8577****
L(0)		12405.26		-12405.26	
$L(\widehat{\beta})$		8354.584		-8168.669	
ρ^2		0.327		0.342	
Number of observations		678		672	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 3-6. The market share of PT in the segmented model B2 of using dummy variables (Convenience importance) (see **Appendix Figure 8-7, page 401**)

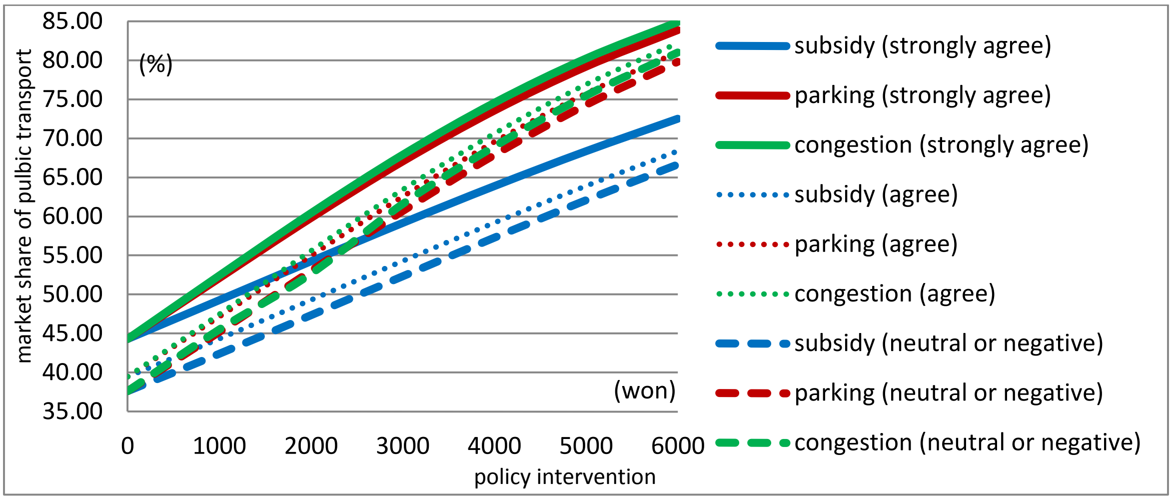


Reference Table 3-6. The coefficients of a segmented model B2 using dummy variables (Time importance) (see **Appendix Table 8-9, page 403**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**0.2298**	**4.2054****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.1998**	**12.4051****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3132**	**-19.4594****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3261**	**-23.2223****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0178**	**3.9648****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0188**	**4.9661****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0210**	**4.9600****
Dummy importance of time 1 (strongly agree:0, agree:1)	β_{time1}			**0.1977**	**4.8020****
Dummy importance of time 2 (strongly agree:0, neutral or others:1)	β_{time2}			**0.2762**	**4.0408****
L(0)		12405.26		-12405.26	
L($\widehat{\beta}$)		8354.584		-8203.512	
ρ^2		0.327		0.339	
Number of observations		678		667	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

Reference Figure 3-7. The market share of PT in the segmented model B2 of using dummy variables (Time importance) (see **Appendix Figure 8-9, page 404**)



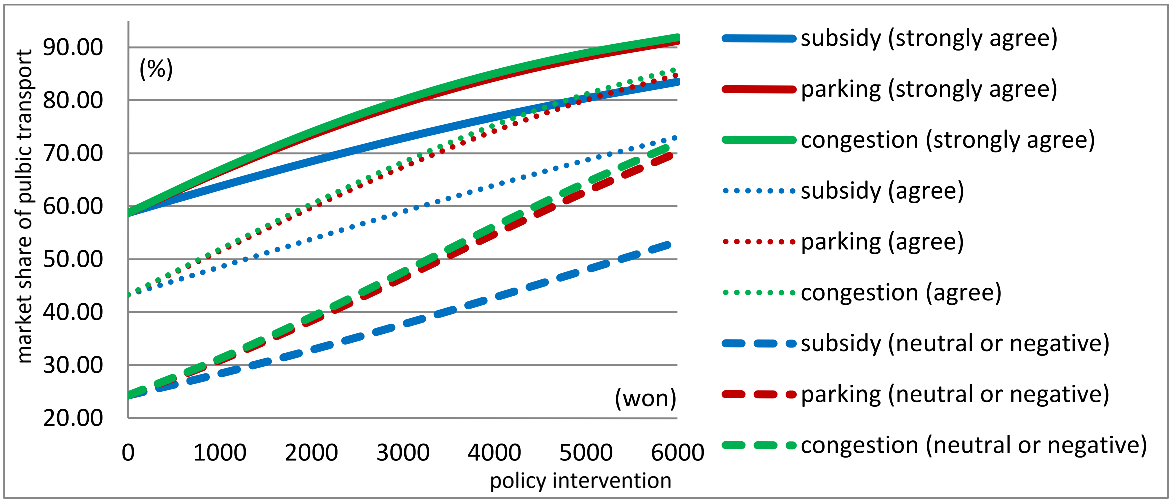
Reference Table 3-7. The coefficients of a segmented model B2 using dummy variables (Cost importance) (see **Appendix Table 8-11, page 406**)

Coefficient		Model B2		Segmentation model	
		Beta	t-value	Beta	t-value
ASC	β_0	**0.3341**	**6.6694****	**-0.3514**	**-5.3344****
PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	**0.2117**	**12.8071****
Additional parking fee	β_2	**-0.3121**	**-19.5858****	**-0.3323**	**-20.0438****
Congestion charge	β_3	**-0.3253**	**-23.3928****	**-0.3468**	**-23.9650****
Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	**0.0187**	**4.0954****
Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	**0.0201**	**5.2321****
Parking & Congestion	β_{23}	**0.0213**	**5.0954****	**0.0228**	**5.2611****
Dummy importance of cost 1 (strongly agree:0, agree:1)	β_{cost1}			**0.6240**	**10.9039****
Dummy importance of cost 2 (strongly agree:0, neutral or others:1)	β_{cost2}			**1.4898**	**25.1535****
L(0)		12405.26		-12405.26	
L($\hat{\beta}$)		8354.584		-7794.586	
ρ^2		0.327		0.372	
Number of observations		678		666	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

Reference Figure 3-8. The market share of PT in the segmented model B2 of using dummy variables (Cost importance) (see **Appendix Figure 8-11, page 407**)



(2) Segmentation results of the segmented model B2 using separate data of segmented groups with attitudinal variables

The results of segmentation analysis in the segmented model B2, which is a model with interaction terms comprising only statistically significant coefficients, using separate data of segmented groups are almost the same as those of the segmented model B0, which is a model without interaction terms.

In comparison with **Reference Table 4-1** and **Table 7-13 (page 164)**, the ρ^2s of the segmented model B2 (0.377, 0296, and 0.224 respectively) is higher than those of the semented model B0 (0.373, 0295, and 0.220 respectively). It means that the validity of the segmented model with interaction terms is higher than that of the segmented model without interaction terms.

Reference Table 4-1. The coefficients of segmented models B2 using separate data (Congestion consciousness) (compare **Table 7-13, page 164**)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	0.0910	1.3657	**0.4743**	**5.4335****	**1.0500**	**6.2492****
PT commute cost subsidy	β_1	**0.1747**	**8.6338****	**0.2001**	**7.0710****	**0.2840**	**4.8168****
Additional parking fee	β_2	**-0.3261**	**-14.9843****	**-0.2834**	**-10.3967****	**-0.3276**	**-6.6000****
Congestion charge	β_3	**-0.3264**	**-17.2598****	**-0.3086**	**-12.9443****	**-0.3556**	**-8.2916****
Subsidy & Parking	β_{12}	**0.0222**	**4.1157****	0.0083	1.0190	0.0093	0.5659
Subsidy & Congestion	β_{13}	**0.0225**	**5.0206****	0.0083	1.1851	0.0135	0.9678
Parking & Congestion	β_{23}	**0.0195**	**3.2681****	**0.0182**	**2.6037****	**0.0351**	**2.9580****
L(0)		-6948.107		-4160.269		-1223.405	
L($\widehat{\beta}$)		-4330.46		-2928.64		-949.1019	
ρ^2		0.377		0.296		0.224	
Number of observations		417		269		77	

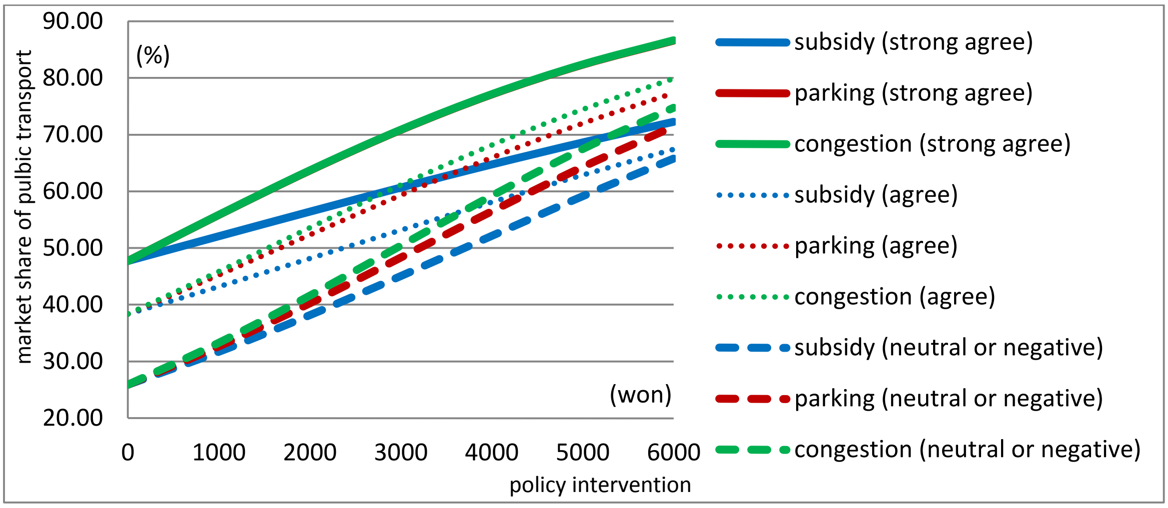
* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.

The position of the intercept for each segmented group in the segmented model B2 is almost the same as that of the segmented model B0. For example, the position of the intercept of the segmented variable in **Reference Figure 4-1** is similar to that of **Figure 7-5 (page 165)**.

The order of the modal shift effect of each MSP in **Reference Figure 4-1** is similar to that of **Figure 7-5 (page 165)**. In many cases, the greatest level of modal shift would be achieved by the introduction of congestion charges, with additional parking fees the next most effective, and the lowest level of modal shift generated by the PT commuting cost subsidies.

In conclusion, the results of segmentation analyses for all the attitudinal segments are similar to those of model B0 in terms of the position of the intercept and the modal shift effect of the MSP.

Reference Figure 4-1. The market share of PT in the segmented model B2 of using separate data of segmented groups (Congestion consciousness) (compare **Figure 7-5, page 165**)

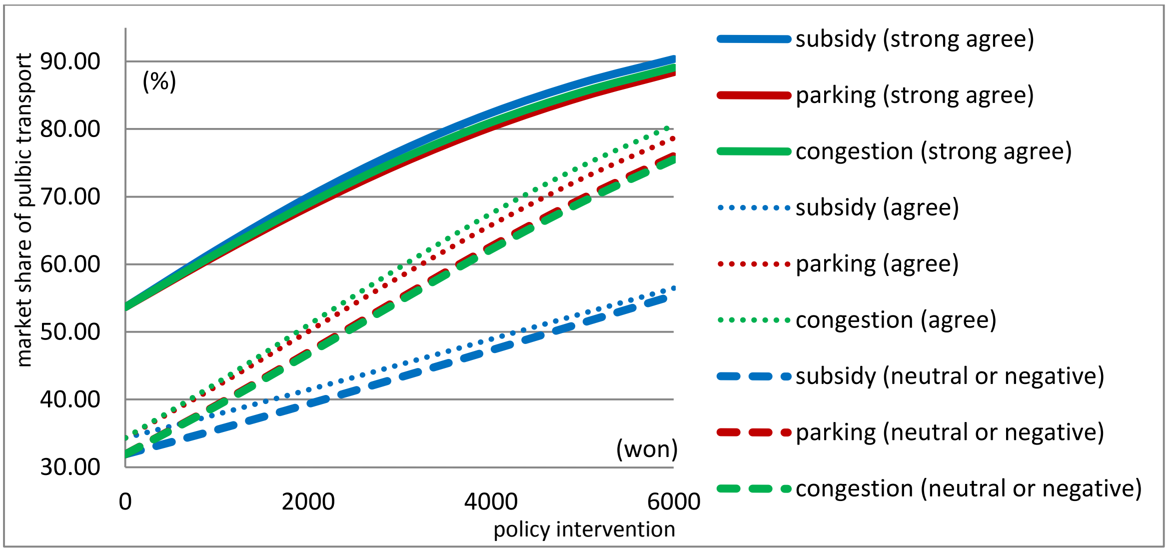


Reference Table 4-2. The coefficients of segmented models B2 using separate data (Environmental consciousness) (see **Appendix Table 8-2, page 392**)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	-0.1467	-1.6220	**0.6487**	**8.9308****	**0.7580**	**5.8416****
PT commute cost subsidy	β_1	**0.3490**	**9.1981****	**0.1515**	**7.4193****	**0.1625**	**4.1467****
Additional parking fee	β_2	**-0.3140**	**-10.0618****	**-0.3258**	**-14.6646****	**-0.3185**	**-8.0804****
Congestion charge	β_3	**-0.3256**	**-11.7428****	**-0.3448**	**-17.8146****	**-0.3141**	**-9.3424****
Subsidy & Parking	β_{12}	**0.0259**	**2.2348***	**0.0146**	**2.7470****	0.0097	0.8902
Subsidy & Congestion	β_{13}	0.0150	1.4664	**0.0186**	**4.2114****	0.0095	1.0412
Parking & Congestion	β_{23}	0.0131	1.4583	**0.0247**	**4.2760****	**0.0269**	**2.8082****
L(0)		-4795.885		-5515.372		-1852.782	
$L(\widehat{\beta})$		-2229.313		-4150.16		-1454.003	
ρ^2		0.535		0.248		0.215	
Number of observations		287		353		114	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 4-2. The market share of PT in the segmented model B2 of using separate data of segmented groups (Environmental consciousness) (see **Appendix Figure 8-2, page 393**)

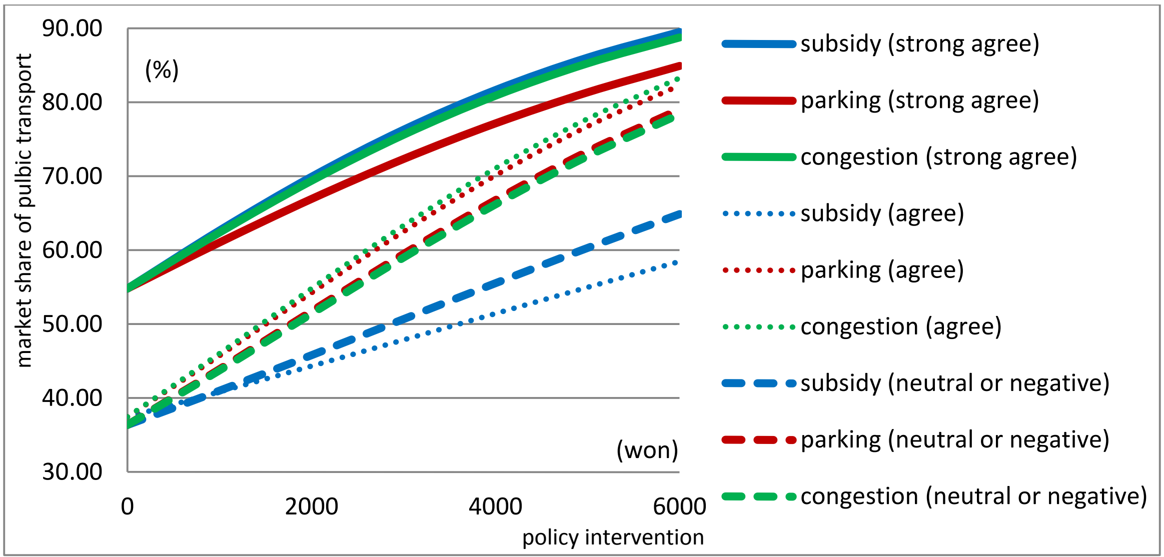


Reference Table 4-3. The coefficients of segmented models B2 using0 separate data (Health consciousness) (see **Appendix Table 8-4, page 396**)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	-0.1920	-1.8584	**0.5132**	**6.0231****	**0.5603**	**6.7907****
PT commute cost subsidy	β_1	**0.3254**	**8.0279****	**0.1425**	**5.9553****	**0.1958**	**7.2473****
Additional parking fee	β_2	**-0.2565**	**-7.5829****	**-0.3413**	**-12.9302****	**-0.3147**	**-12.0999****
Congestion charge	β_3	**-0.3131**	**-10.2136****	**-0.3531**	**-15.3010****	**-0.3080**	**-13.7915****
Subsidy & Parking	β_{12}	0.0181	1.5864	**0.0199**	**3.4088****	0.0056	0.6991
Subsidy & Congestion	β_{13}	**0.0309**	**3.2394****	**0.0214**	**4.4148****	0.0012	0.1673
Parking & Congestion	β_{23}	**0.0187**	**2.0107***	**0.0242**	**3.3835****	**0.0227**	**3.4610****
L(0)		-3474.054		-3880.931		-4771.625	
$L(\widehat{\beta})$		-1824.139		-2797.393		-3345.477	
ρ^2		0.475		0.279		0.299	
Number of observations		211		248		293	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 4-3. The market share of PT in the segmented model B2 of using separate data of segmented groups (Health consciousness) (see **Appendix Figure 8-4, page 396**)

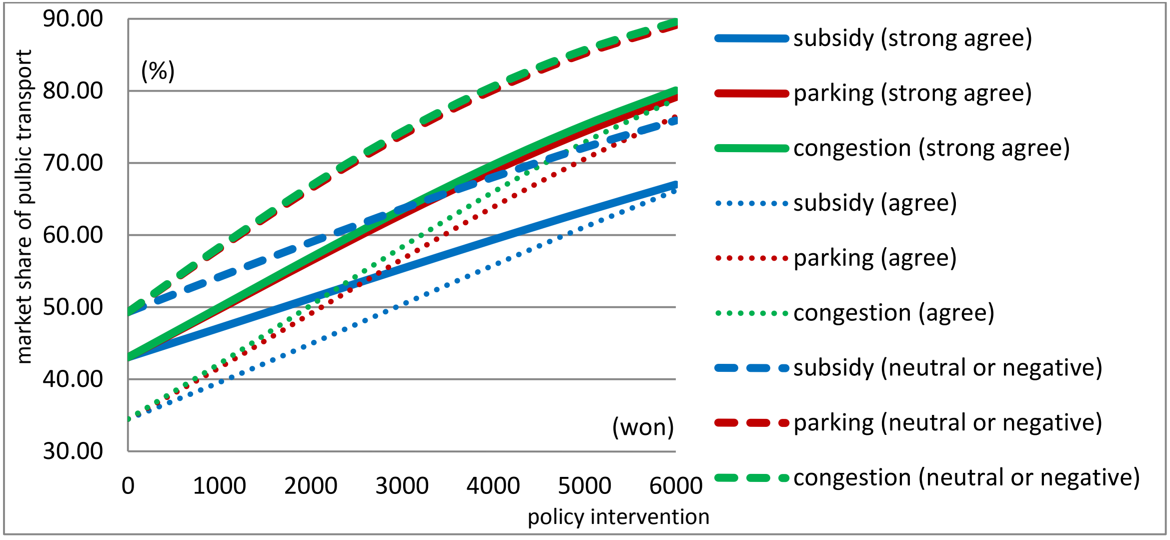


Reference Table 4-4. The coefficients of segmented models B2 using separate data (Freedom consciousness) (see **Appendix Table 8-6, page 398**)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**0.2799**	**2.8003****	**0.6425**	**7.8215****	0.0268	0.3119
PT commute cost subsidy	β_1	**0.1646**	**5.5238****	**0.2187**	**8.3683****	**0.1954**	**6.8898****
Additional parking fee	β_2	**-0.2686**	**-8.5743****	**-0.3032**	**-12.0102****	**-0.3552**	**-12.3707****
Congestion charge	β_3	**-0.2783**	**-10.2884****	**-0.3259**	**-14.8286****	**-0.3632**	**-14.3199****
Subsidy & Parking	β_{12}	0.0059	0.7070	0.0124	1.6772	**0.0290**	**3.9736****
Subsidy & Congestion	β_{13}	0.0122	1.7475	**0.0126**	**1.9894***	**0.0271**	**4.4964****
Parking & Congestion	β_{23}	**0.0259**	**3.3117****	**0.0192**	**3.0084****	0.0129	1.5065
L(0)		-3026.281		-4839.554		-4260.776	
$L(\widehat{\beta})$		-2205.423		-3479.304		-2370.703	
ρ^2		0.271		0.281		0.444	
Number of observations		198		298		255	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 4-4. The market share of PT in the segmented model B2 of using separate data of segmented groups (Freedom consciousness) (see **Appendix Figure 8-6, page 399**)

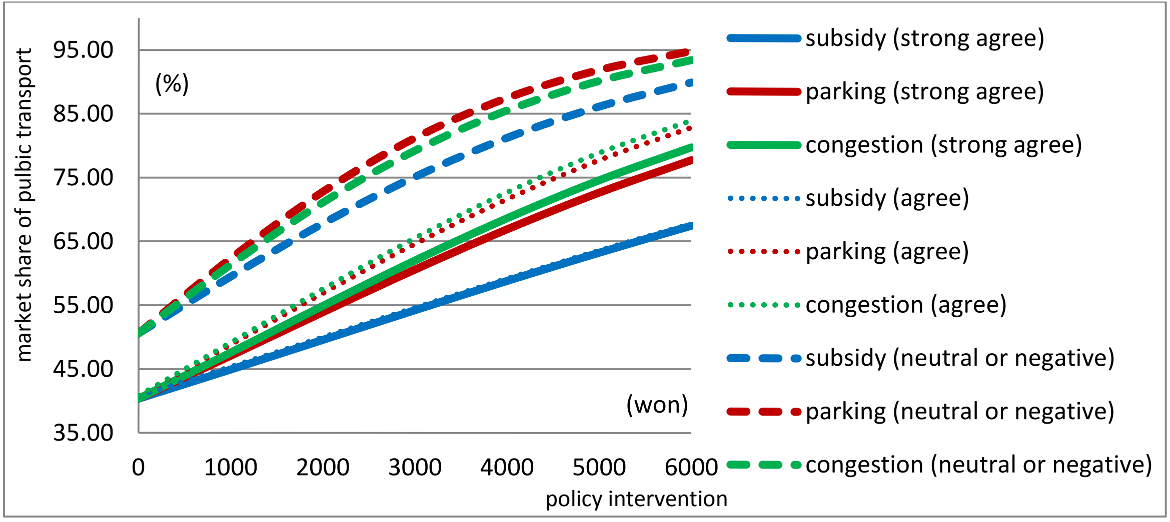


Reference Table 4-5. The coefficients of segmented models B2 using separate data (Convenience importance) (see **Appendix Table 8-8, page 401**)

Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**0.3917**	**5.3349****	**0.3720**	**4.8753****	-0.0221	-0.1299
PT commute cost subsidy	β_1	**0.1868**	**8.1342****	**0.1858**	**8.0890****	**0.3608**	**4.8804****
Additional parking fee	β_2	**-0.2738**	**-11.9407****	**-0.3243**	**-13.4458****	**-0.4798**	**-7.2461****
Congestion charge	β_3	**-0.2937**	**-14.7344****	**-0.3378**	**-16.0351****	**-0.4387**	**-7.6059****
Subsidy & Parking	β_{12}	0.0084	1.2778	**0.0214**	**3.5688****	0.0337	1.3122
Subsidy & Congestion	β_{13}	**0.0116**	**2.0951***	**0.0213**	**4.2815****	0.0186	0.8306
Parking & Congestion	β_{23}	**0.0157**	**2.6783****	**0.0236**	**3.6482****	**0.0455**	**2.3691***
L(0)		-5807.187		-5040.566		-1446.598	
$L(\widehat{\beta})$		-4118.039		-3462.554		-570.1701	
ρ^2		0.291		0.313		0.606	
Number of observations		368		314		79	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

Reference Figure 4-5. The market share of PT in the segmented model B2 of using separate data of segmented groups (Convenience importance) (see **Appendix Figure 8-8, page 402**)



Reference Table 4-6. The coefficients of segmented models B2 using separate data (time importance) (see **Appendix Table 8-10, page 404**)

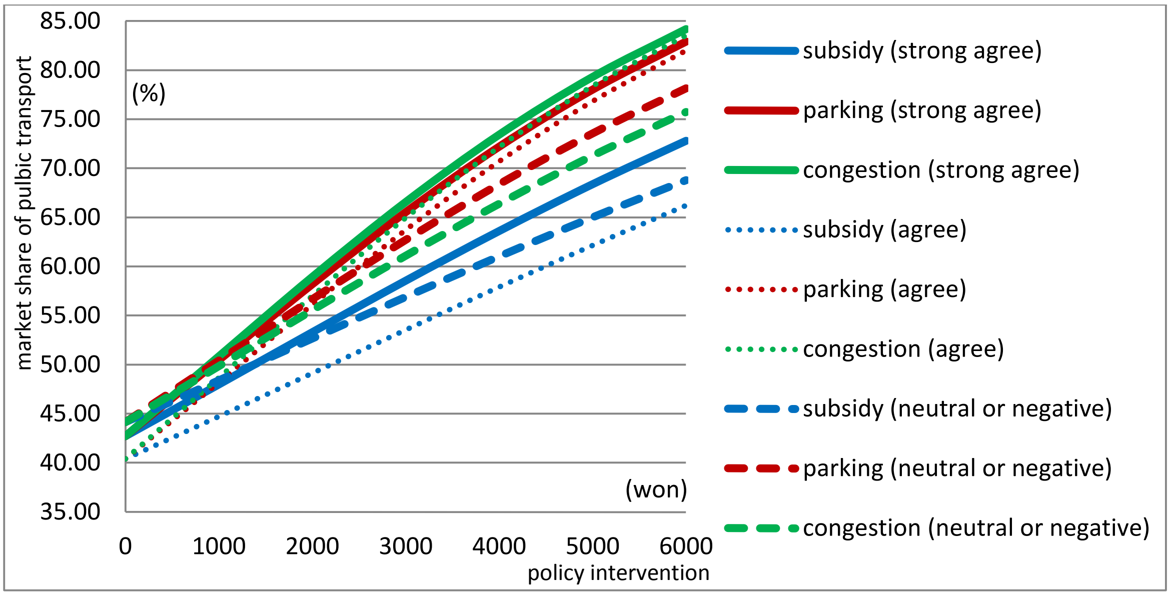
Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	**0.2937**	**3.9413****	**0.3894**	**5.2004****	0.2350	1.3988
PT commute cost subsidy	β_1	**0.2130**	**8.7933****	**0.1771**	**7.6999****	**0.1708**	**3.2028****
Additional parking fee	β_2	**-0.3119**	**-12.9250****	**-0.3174**	**-13.5718****	**-0.2514**	**-4.7629****
Congestion charge	β_3	**-0.3274**	**-15.4593****	**-0.3353**	**-16.4163****	**-0.2289**	**-5.1456****
Subsidy & Parking	β_{12}	0.0138	1.9381	**0.0197**	**3.3269****	0.0045	0.2926
Subsidy & Congestion	β_{13}	**0.0131**	**2.1445***	**0.0234**	**4.8087****	-0.0035	-0.2658
Parking & Congestion	β_{23}	**0.0208**	**3.2350****	**0.0200**	**3.1903****	0.0210	1.6452
L(0)		-5827.981		-5247.817		-1127.75	
$L(\widehat{\beta})$		-3697.774		-3665.483		-823.4616	
ρ^2		0.366		0.302		0.270	
Number of observations		355		331		70	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

* Superscript * represents significance within 5%.

Reference Figure 4-6. The market share of PT in the segmented model B2 of using separate data of segmented groups (Time importance) (see **Appendix Figure 8-10, page 405**)



Reference Table 4-7. The coefficients of segmented models B2 using separate data (Cost importance) (see **Appendix Table 8-12, page 407**)

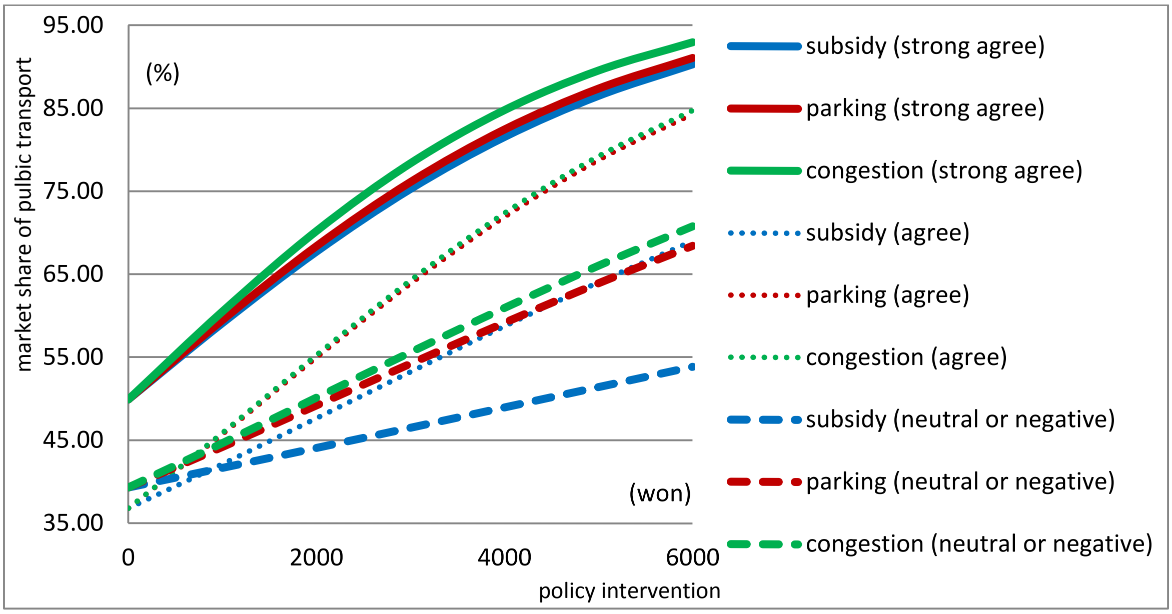
Classification		Strongly agree		Agree		Neutral or others	
		Beta	t-value	Beta	t-value	Beta	t-value
ASC	β_0	0.0041	0.0371	**0.5423**	**6.9884****	**0.4345**	**4.9232****
PT commute cost subsidy	β_1	**0.3725**	**8.1098****	**0.2236**	**8.5469****	**0.0981**	**4.2298****
Additional parking fee	β_2	**-0.3876**	**-9.8848****	**-0.3706**	**-14.3743****	**-0.2011**	**-7.7093****
Congestion charge	β_3	**-0.4304**	**-11.8838****	**-0.3763**	**-16.5357****	**-0.2198**	**-9.8972****
Subsidy & Parking	β_{12}	**0.0312**	**2.2778***	0.0092	1.0855	0.0090	1.5998
Subsidy & Congestion	β_{13}	**0.0407**	**3.5339****	0.0046	0.6195	**0.0112**	**2.3774***
Parking & Congestion	β_{23}	**0.0386**	**3.3775****	0.0147	2.0209*	0.0099	1.5447
L(0)		-3091.436		-5683.807		-3409.591	
$L(\widehat{\beta})$		-1398.154		-3339.665		-2969.876	
ρ^2		0.548		0.412		0.129	
Number of observations		181		356		218	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

* Superscript * represents significance within 5%.

Reference Figure 4-7. The market share of PT in the segmented model B2 of using separate data of segmented groups (Cost importance) (see **Appendix Figure 8-12, page 408**)



Appendix 9. Application of the Rule of Half Convention

The Rule of Half convention (RoH) as a measurement of the change in the CS can be applied only for small cost change and only if the demand curve is a straight line. Since the implicit demand curves in the research of transportation are not straight lines, RoH may be considered as only a rough approximation of the change of welfare benefit (Jong et al., 2007). That is, RoH may overestimate changes in the CS since the demand curve is convex to the origin.

In transportation, it is possible to calculate the welfare benefit of a policy intervention through a change in the MCS in combination with the assumption of a linear demand curve. Two main components to the calculation are comprised of the generalised cost of transport and demand for transport before and after policy intervention. In general, as the generalised cost of transport drops, demand goes up along the demand curve. The generalised cost of an MSP can be taken by the amount of input value of the MSP. Also, the demand curve indicates the demand at different levels of generalised cost (Scottish government, 2009). The demand before and after policy intervention can stem from the values of the utility function depending on the particular context of the policy intervention.

Thus, area $P_{X1}\mathrm{AD}P_{X2}$ in **Figure 8-1 (page 180)** can be measured as a linear approximation to the Marshallian demand curve between the generalised cost before and after policy intervention. That is, in order to calculate the CS, it should be assumed that Marshallian demand curve is linear. In addition, in order to compare the change in the CS (ΔCS) and the one of the CV, model B0 is applied. The change in the CS, area $P_{X1}\mathrm{AD}P_{X2}$ in **Figure 8-1 (page 180)**, can be estimated using **Equation Appendix 9-1** (Preston and Almutairi, 2013; Williams, 1977; Laird, 2009).

$$\Delta\mathrm{CS} = \frac{1}{2}(X_2 + X_1)(P_{X1} - P_{X2})$$
$$\Delta\mathrm{CS} = \frac{1}{2}(X_{before\ MSP} + X_{after\ MSP})(P_{before\ MSP} - P_{after\ MSP}) \qquad \text{(Appendix 9-1)}$$

To easily compare the CS (ΔCS) using RoH with the CV using Small and Rosen's formula, the log sum value of the utility in **Equation 8-1 (page 182)** are used. The calculation process of logarithm values from the utility function is the same as Small and Rosen's calculation (see **Chapter 8**, **page 186-188**). For the low income group, the log sum values of the utility before (0.593649) and after (1.54540) implementation of the PT commuting cost subsidy with 5,000 won are used (**see Equation 8-14, page 187**). That is, the point estimate before the implementation of the PT commuting cost subsidy on the demand curve is 0.593649, while the point estimate after the implementation of the PT commuting cost subsidy is 1.154540. In **Figure 8-1 (page 180)**, X_1 is 0.593649, while X_2 is

1.154540, X_3 is unknown. The values of the differences between the logsum before and after the MSP ([In $\sum_{k=1}^{2} U_i^1$ + In$\sum_{k=1}^{2} U_i^0$]) can denote (X_1 + X_2) in **Figure 8-1 (page 180)**.

Also, the difference in value before and after the MSP is 5. Since model B0 is based on the monetary unit 1 (meaning 1,000 won), the implementation of a PT commuting cost subsidy worth 5,000 won can be represented as 5. The generalised cost of transport before the MSP can be expressed as 0, while the one after the MSP can be denoted as five (5). Since the PT commuting cost subsidy is a policy intervention of giving economic advantages or benefits for commuters, a positive value should be reflected as a plus five (5) in the formula.

$$\Delta \text{CS} = \frac{1}{2}(0.593649 + 1.154540)(0 - 5) = -\mathbf{4.370474} \quad \text{(Appendix 9-2)}$$

As can be seen in **Equation Appendix 9-2**, the change in the CS before and after the implementation of the PT commuting cost subsidy worth 5,000 won can be calculated as – **4.370474**. In a comparison of the sign in **Appendix Table 9-1** and **Table 8-5 (page 188)**, the CS is equal to the CV. That is, in the case of the PT commuting cost subsidy, the minus signs mean that the implementation of this policy will be beneficial to the consumer. In addition, since the value of welfare changes in the CS (for example, see **– 4,370.47** won in **Appendix Table 9-1**) using RoH (ΔCS) is much higher than that of the CV (see **– 3,262.89** won in **Table 8-5, page 188**), it can be clearly understood that welfare changes in the CS using RoH (ΔCS) are overestimated. In general, if the change in generalised cost is large and income is low, the change in the CS using RoH (ΔCS) can be overestimated. This result seems to correspond to the existing studies (Scottish government, 2009). Therefore, this method has a limitation to be applied in a welfare measurement.

Appendix Table 9-1. Consumer surplus using RoH (ΔCS) (compare **Table 8-5, page 188**)

Type of MSP	Degree of policy intervention	Low Income group	Middle Income group	High Income group	Average
Subsidy	1,000 won (=£ 0.56)	-642.934	-820.549	-975.941	-759.737
	2,000 won (=£1.11)	-1,391.55	-1,667.03	-2,013.23	-1,582.17
	3,000 won (=£1.67)	-2,256.12	-2,540.61	-3,119.14	-2,472.59
	4,000 won (=£2.22)	-3,246.2	-3,442.43	-4,301.02	-3,436.18
	5,000 won (=£2.78)	**-4,370.47**	-4,373.66	-5,566.17	-4,477.97
Parking	1,000 won (=£ 0.56)	544.15	742.87	884.55	674.17
	2,000 won (=£1.11)	1,002.58	1,370.97	1,654.29	1,249.34
	3,000 won (=£1.67)	1,393.94	1,907.01	2,326.54	1,744.38
	4,000 won (=£2.22)	1,734.77	2,372.25	2,918.45	2,176.79
	5,000 won (=£2.78)	2,039.14	2,785.62	3,446.30	2,562.16
Congestion	1,000 won (=£ 0.56)	543.45	732.06	882.20	670.18
	2,000 won (=£1.11)	1,000.16	1,333.70	1,645.81	1,235.39
	3,000 won (=£1.67)	1,389.34	1,835.98	2,309.54	1,717.33
	4,000 won (=£2.22)	1,727.91	2,267.06	2,891.81	2,135.89
	5,000 won (=£2.78)	2,030.24	2,650.74	3,410.04	2,508.42

* Since number 1 means 1,000 won. Therefore, to understand the context, the values are multiplied by 1,000 won.

<Reference Data 3> Result of equity assessment by applying model B2

(1) Equity assessment in the segmented models B2 using separate date of each income group

The equity assessment analysis in the segmented models B2 using separate data of each income groups (i.e. low, middle, and high) can be carried out by applying Small and Rose's formula (see **Equation 8-1, page 182**) like model B0. The coefficients of one income group in **Reference Table 5-1** are different from those of the other income group. The calculation processes of the CV for each income group in model B2 are the same as those of model B0.

Reference Table 5-1. The coefficients in the segmented model B2s using separate data of each income group

Classification	Coefficient	Beta	Value	t-value	Goodness of fit
Low-income group	ASC	β_0	0.0319	0.4126	L(0) = - 5771.143
	PT commuting cost subsidy	β_1	**0.2423**	**8.9853****	L($\widehat{\beta}$)= - 3290.511
	Additional parking fee	β_2	**-0.3254**	**-12.5363****	ρ^2= 0.498
	Congestion charge	β_3	**-0.3222**	**-14.2534****	Number of observations: 343
	Subsidy & Parking	β_{12}	**0.0172**	**2.1514***	
	Subsidy & Congestion	β_{13}	**0.0168**	**2.4716***	
	Parking & Congestion	β_{23}	**0.0275**	**3.9863****	
Middle-income group	ASC	β_0	**0.4974**	**5.5534****	L(0) = - 3636.35
	PT commuting cost subsidy	β_1	**0.1520**	**5.9589****	L($\widehat{\beta}$)= - 2507.136
	Additional parking fee	β_2	**-0.3231**	**-11.6716****	ρ^2= 0.311
	Congestion charge	β_3	**-0.3703**	**-15.0012****	Number of observations: 225
	Subsidy & Parking	β_{12}	**0.0189**	**2.9401****	
	Subsidy & Congestion	β_{13}	**0.0212**	**4.0067****	
	Parking & Congestion	β_{23}	**0.0155**	**1.9989***	
High-income group	ASC	β_0	**0.7283**	**7.1680****	L(0) = - 2945.182
	PT commuting cost subsidy	β_1	**0.2123**	**6.5693****	L($\widehat{\beta}$)= - 2314.397
	Additional parking fee	β_2	**-0.3032**	**-9.8655****	ρ^2= 0.214
	Congestion charge	β_3	**-0.3025**	**-11.5153****	Number of observations: 196
	Subsidy & Parking	β_{12}	0.0159	1.8205	
	Subsidy & Congestion	β_{13}	**0.0152**	**2.0650***	
	Parking & Congestion	β_{23}	**0.0236**	**3.1274****	
Overall (low+middle +high income group)	ASC	β_0	**0.3342**	**6.6694****	L(0) = - 12405.26
	PT commuting cost subsidy	β_1	**0.2015**	**12.6604****	L($\widehat{\beta}$)= - 354.584
	Additional parking fee	β_2	**-0.3121**	**-19.5858****	ρ^2= 0.327
	Congestion charge	β_3	**-0.3253**	**-23.3928****	Number of observations: 764
	Subsidy & Parking	β_{12}	**0.0186**	**4.2060****	
	Subsidy & Congestion	β_{13}	**0.0189**	**5.0818****	
	Parking & Congestion	β_{23}	**0.0213**	**5.0954****	

* The bold figures mean that the coefficient is statistically significant.
* Superscript ** represents significance within 1%.
* Superscript * represents significance within 5%.

The results of the equity assessment analysis in the segmented models B2 using separate data of each income group are almost the same as those of model B0. That is, the CVPP of MSP for each income group in model B2 (see **Reference Table 5-2**) is almost the same as that of model B0 (see **Table 8-5**, **page 188**).

Reference Table 5-2. The CVPP of MSP in the segmented models B2 using separate data of each income group (unit: won)

Type of MSP	Degree of policy intervention	Low income group	Middle income group	High income group	Average
Subsidy	1,000 won (=£0.56)	-522.27	-396.23	-349.42	-441.97
	2,000 won (=£1.11)	-1104.31	-829.32	-748.46	-934.02
	3,000 won (=£1.67)	-1743.80	-1300.01	-1199.28	-1476.29
	4,000 won (=£2.22)	-2437.02	-1808.66	-1702.96	-2067.96
	5,000 won (=£2.78)	-3179.19	-2355.15	-2259.43	-2707.22
Parking	1,000 won (=£ 0.56)	467.42	583.01	640.06	544.31
	2,000 won (=£1.11)	855.54	1086.19	1207.89	1010.91
	3,000 won (=£1.67)	1169.87	1509.38	1700.47	1401.40
	4,000 won (=£2.22)	1418.71	1856.41	2118.16	1720.74
	5,000 won (=£2.78)	1611.86	2134.37	2464.56	1976.46
Congestion	1,000 won (=£ 0.56)	467.81	577.22	640.14	542.66
	2,000 won (=£1.11)	857.07	1062.75	1208.22	1004.36
	3,000 won (=£1.67)	1173.11	1457.56	1701.25	1387.06
	4,000 won (=£2.22)	1424.05	1768.34	2119.53	1696.49
	5,000 won (=£2.78)	1619.44	2005.92	2466.64	1941.11

(2) Equity assessment in the segmented model B2 using income dummy variables

The equity assessment analysis in the segmented model B2 (see **Reference Table 5-3**) using income dummy variables can be carried out by applying Small and Rose's formula (see **Equation 8-1, page 182**) like model B0. The calculation processes of the CVPP for each income group in model B2 are the same as those of model B0.

Reference Table 5-3. The coefficients of the segmented model B2 using income dummy variables

Coefficient	Beta	Value	t-value	Goodness of fit
ASC	β_0	-0.0103	-0.1866	
PT commute cost subsidy	β_1	**0.2066**	**12.7257****	
Additional parking fee	β_2	**-0.3220**	**-19.8873****	L(0) = -12405.26
Congestion charge	β_3	**-0.3348**	**-23.7048****	L($\widehat{\beta}$)= - 8134.466
Subsidy & Parking	β_{12}	**0.0194**	**4.3113****	ρ^2= 0.3443
Subsidy & Congestion	β_{13}	**0.0195**	**5.1367****	Number of
Parking & Congestion	β_{23}	**0.0229**	**5.4137****	observations: 764
Middle income (low income:0, middle income:1)	$\beta_{middle\ income}$	**0.5094**	**10.8339****	
High income (low income:0, high income:1)	$\beta_{high\ income}$	**0.8221**	**17.0512****	

* The bold figures mean that the coefficient is statistically significant.

* Superscript ** represents significance within 1%.

The results of the equity assessment analysis in the segmented model B2 using income dummy variables are almost the same as those of model B0. That is, the CVPP of the MSP for each segmented income group in model B2 (see **Reference Table 5-4**) is almost the same as that of model B0 (see **Table 8-7, page 191**).

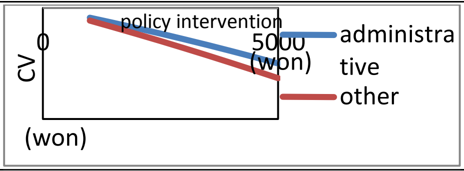
Reference Table 5-4. The CVPP of the MSP in the segmented models B2 using the income dummy variables (unit: won)

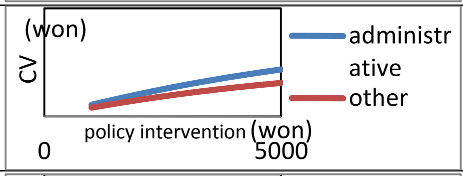
Type of MSP	Degree of policy intervention	Low-income group	Middle-income group	High-income group
Subsidy	1,000 won (=£0.56)	-528.34	-402.41	-330.06
	2,000 won (=£1.11)	-1107.65	-855.29	-707.26
	3,000 won (=£1.67)	-1736.28	-1359.63	-1134.03
	4,000 won (=£2.22)	-2411.69	-1915.35	-1611.89
	5,000 won (=£2.78)	-3130.63	-2521.28	-2141.31
Parking	1,000 won (=£0.56)	457.37	583.55	656.89
	2,000 won (=£1.11)	836.73	1087.57	1238.18
	3,000 won (=£1.67)	1143.85	1511.85	1739.88
	4,000 won (=£2.22)	1387.07	1860.13	2161.89
	5,000 won (=£2.78)	1576.06	2139.42	2508.07
Congestion	1,000 won (=£0.56)	455.79	581.99	655.42
	2,000 won (=£1.11)	830.68	1081.21	1232.03
	3,000 won (=£1.67)	1131.07	1497.72	1725.75
	4,000 won (=£2.22)	1366.19	1835.95	2136.91
	5,000 won (=£2.78)	1546.54	2103.85	2470.22

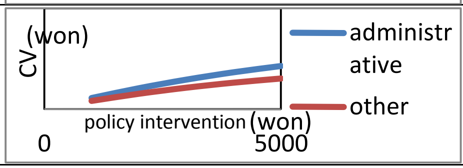
Appendix 10. The Compensating Variation Per Person (CVPP) of Modal Shift Policies in the Diverse Segmented Variables

Occupation

MSP	policy intervention	Administrative	other
Subsidy	1,000	-438	-575
	2,000	-906	-1,179
	3,000	-1,405	-1,813
	4,000	-1,935	-2,474
	5,000	-2,494	-3,162
Parking	1,000	549	412
	2,000	1,040	769
	3,000	1,473	1,076
	4,000	1,851	1,335
	5,000	2,177	1,553
Congestion	1,000	546	410
	2,000	1,031	762
	3,000	1,454	1,059
	4,000	1,818	1,307
	5,000	2,127	1,512

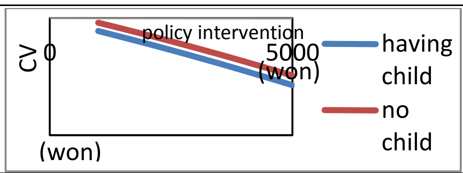


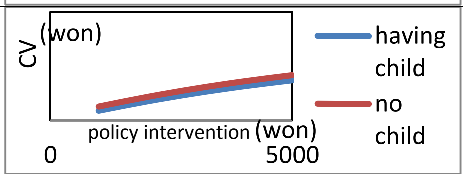


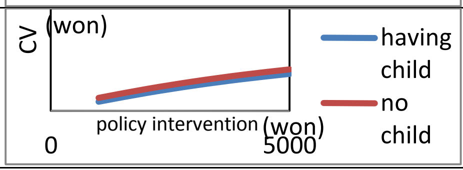


Whether having a child

MSP	policy intervention	Child	no child
Subsidy	1,000	-554	-194
	2,000	-1,087	-713
	3,000	-1,648	-1,261
	4,000	-2,237	-1,838
	5,000	-2,855	-2,443
Parking	1,000	457	647
	2,000	883	1,087
	3,000	1,255	1,471
	4,000	1,575	1,803
	5,000	1,848	2,086
Congestion	1,000	456	634
	2,000	876	1,067
	3,000	1,238	1,441
	4,000	1,545	1,759
	5,000	1,802	2,027

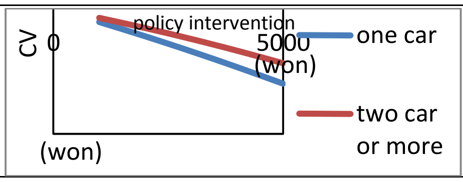


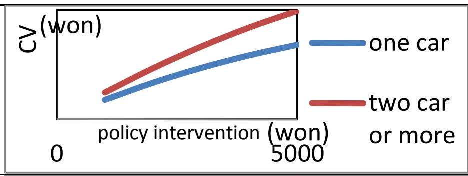
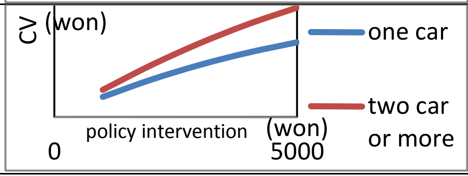




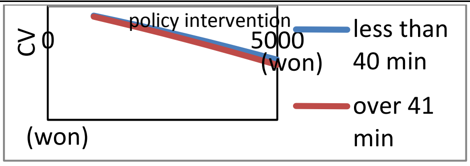
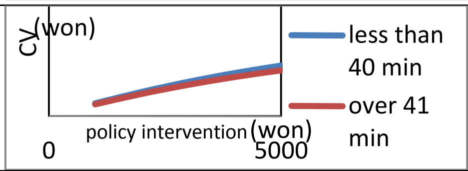
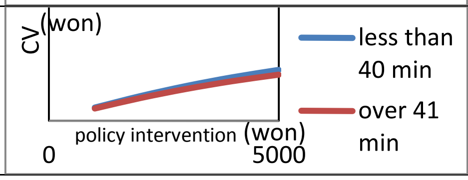
Number of cars

MSP	policy intervention	one car	two cars+
Subsidy	1,000	-539	-376
	2,000	-1,109	-783
	3,000	-1,710	-1,220
	4,000	-2,341	-1,688
	5,000	-3,000	-2,188

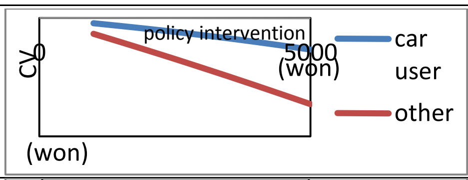
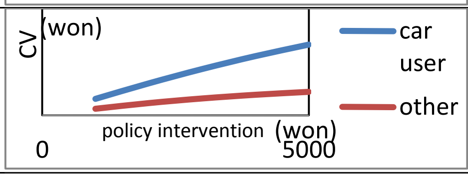
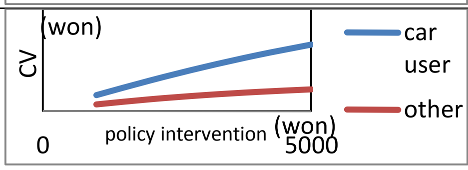


Parking	1,000	448	611	
	2,000	839	1,165	
	3,000	1,176	1,662	
	4,000	1,464	2,100	
	5,000	1,706	2,483	
Congestion	1,000	446	609	
	2,000	830	1,157	
	3,000	1,158	1,642	
	4,000	1,433	2,065	
	5,000	1,660	2,429	

Commute time of car users

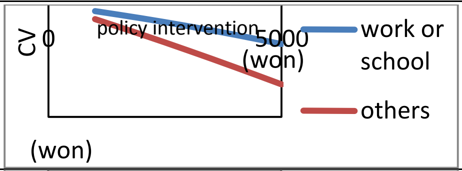
MSP	policy intervention	less than 40 min	over 41 min	
Subsidy	1,000	-412	-456	
	2,000	-853	-942	
	3,000	-1,324	-1,459	
	4,000	-1,825	-2,005	
	5,000	-2,356	-2,582	
Parking	1,000	574	529	
	2,000	1,088	998	
	3,000	1,543	1,408	
	4,000	1,939	1,762	
	5,000	2,280	2,062	
Congestion	1,000	572	527	
	2,000	1,080	989	
	3,000	1,523	1,389	
	4,000	1,905	1,728	
	5,000	2,227	2,012	

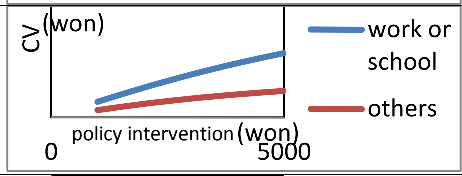
Main commute mode

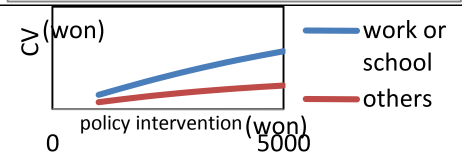
MSP	policy intervention	car user	other	
Subsidy	1,000	-213	-670	
	2,000	-451	-1,369	
	3,000	-715	-2,098	
	4,000	-1,008	-2,853	
	5,000	-1,329	-3,633	
Parking	1,000	775	316	
	2,000	1,499	577	
	3,000	2,166	788	
	4,000	2,770	958	
	5,000	3,307	1,093	
Congestion	1,000	773	314	
	2,000	1,492	569	
	3,000	2,148	773	
	4,000	2,736	934	
	5,000	3,253	1,059	

The purpose of car use

MSP	Policy intervention	work or school	others
Subsidy	1,000	-293	-655
	2,000	-615	-1,339
	3,000	-967	-2,052
	4,000	-1,350	-2,791
	5,000	-1,765	-3,556
Parking	1,000	694	332
	2,000	1,332	610
	3,000	1,910	841
	4,000	2,425	1,030
	5,000	2,878	1,183
Congestion	1,000	692	330
	2,000	1,323	602
	3,000	1,889	825
	4,000	2,387	1,003
	5,000	2,817	1,145

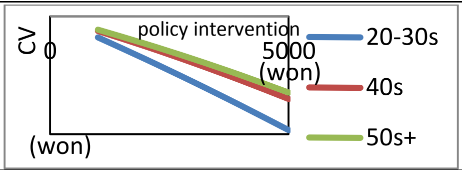


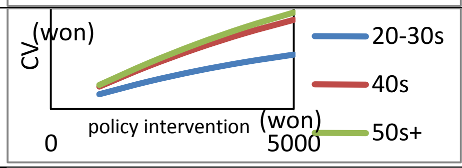


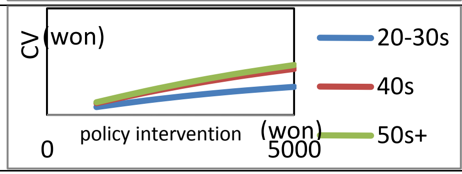


Age

MSP	Policy intervention	20-30s	40s	50s+
Subsidy	1,000	-620	-429	-391
	2,000	-1,270	-889	-813
	3,000	-1,947	-1,379	-1,265
	4,000	-2,651	-1,902	-1,749
	5,000	-3,380	-2,455	-2,263
Parking	1,000	367	558	595
	2,000	681	1,056	1,133
	3,000	946	1,496	1,611
	4,000	1,168	1,879	2,031
	5,000	1,352	2,208	2,395
Congestion	1,000	365	555	593
	2,000	673	1,048	1,124
	3,000	931	1,478	1,592
	4,000	1,143	1,847	1,998
	5,000	1,316	2,160	2,345

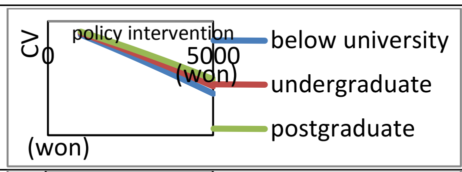


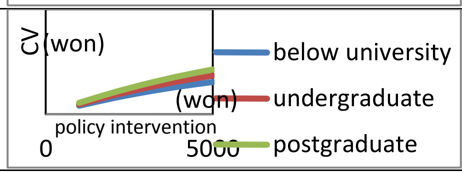




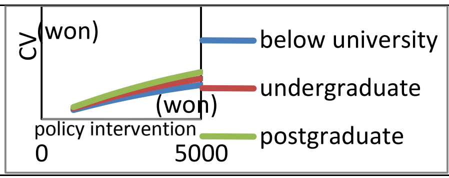
Education

MSP	policy intervention	below university	under graduate	post graduate
Subsidy	1,000	-579	-512	-450
	2,000	-1,186	-1,053	-930
	3,000	-1,821	-1,623	-1,439
	4,000	-2,482	-2,222	-1,977
	5,000	-3,170	-2,848	-2,544
Parking	1,000	408	474	536
	2,000	762	892	1,015
	3,000	1,066	1,256	1,437
	4,000	1,323	1,569	1,805
	5,000	1,540	1,835	2,122
Congestion	1,000	406	472	534





	2,000	754	884	1,006
	3,000	1,048	1,237	1,418
	4,000	1,294	1,537	1,772
	5,000	1,498	1,788	2,071



Distance

MSP	policy intervention	less than 10km	10.1-20km	more than 20km
Subsidy	1,000	-479	-433	-531
	2,000	-999	-906	-1,102
	3,000	-1,559	-1,420	-1,713
	4,000	-2,159	-1,974	-2,362
	5,000	-2,798	-2,569	-3,047
Parking	1,000	512	559	460
	2,000	967	1,060	864
	3,000	1,364	1,502	1,213
	4,000	1,707	1,889	1,510
	5,000	2,000	2,221	1,762
Congestion	1,000	510	557	458
	2,000	958	1051	856
	3,000	1,345	1,483	1,195
	4,000	1,675	1,856	1,480
	5,000	1,952	2,172	1,718