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FACULTY OF SOCIAL SCIENCES

Department of Economics

Preferences for Air Quality Improvement in China: Evidence from Discrete Choice Experiments

by

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Abstract

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PREFERENCES FOR AIR QUALITY IMPROVEMENT IN CHINA: EVIDENCE FROM DISCRETE CHOICE EXPERIMENTS

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Outdoor air pollution is one of the most detrimental issues to human health, and has triggered massive concern in many cities globally. Due to the public nature of the good, negative externalities caused by air pollution from industrial and individual activities cannot be solved by the market, and the central government has to step in to reduce air pollution. However, governments in developing countries are not always fully incentivised to combat pollution due to concern about reduced economic growth, and governmental action depends on the trade-off between air quality and economic development. To inform this trade-off decision, estimates for both the benefits of air quality improvement and the costs of air quality deterioration are required.

This thesis aims to elicit individuals' preferences for air quality changes using discrete choice experiments. The study area is Beijing, China, where severe air pollution has existed over the last decade. The experimental design involves hypothetical policy scenarios that describe changes in the health and visibility aspects of air pollution, and changes in policy cost (i.e., household energy bills).

The first issue I investigate in the thesis is whether losses from air quality deterioration are larger than gains from air quality improvement. Using a unique gain-loss experimental design that allows to measure utility gains and losses simultaneously, this thesis finds that people place more weight on air quality losses than gains. I also find that social capital plays a role in individuals' preferences for air quality changes, and that it correlates with loss aversion preferences. Additionally, the findings provide evidence of non-compensatory behaviour and unwillingness to trade reduction of air quality for monetary compensation.

Environmental outcomes are often affected by the stochastic nature of the environment and ecosystem, as well as the effectiveness of governmental policy in combination with human activities. The second issue explored in this thesis is whether, and how, individuals incorporate uncertainty around policy outcomes in their decision making. Using a discrete choice experiment where the risk of outcome delivery is included in the design as an additional attribute, I find that respondents' utility decreases when risk increases. However, people treat risk as if it is independent of its related policy outcomes in scenarios of both air quality gain and loss.

Following the investigation of how risk is taken into consideration in a discrete choice experiment, the third topic investigated is whether people's environmental preferences are affected by the effects of risky choice framing. In a new experimental design, where policy is described as risky, the expected outcomes of the policy are set to be equal to those in a certain treatment where outcomes are riskless. The information of expected outcomes is embedded in the attribute to assist decision making. The results suggest that risky framing in policy scenarios has little effect on people's air quality preferences.

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Research Thesis: Declaration of Authorship

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I 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.

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Abbreviations

AIC = Akaike information criterion

ANA = attribute non-attendance

AQI = air quality index

BIC = Bayesian information criterion

CVM = contingent valuation method

DCE = discrete choice experiment

DU = direct risk aversion

ECLC = equality-constrained latent class

EU = expected utility (theory)

IID = independent and identically distributed

MNL = multinomial logit

MXL = mixed logit

PT = prospect theory

SP = stated preference

RP= revealed preference

RRM = random regret minimization

RUM = random utility maximization

WHO = World Health Organisation

PM = particulate matter

Data Access Statement

Bona fide researchers, subject to registration may request supporting data via University of Southampton repository https://doi.org/10.5258/SOTON/D1664

Chapter 1
Introduction

Outdoor air pollution is one of the most notable threats to human health around the world. Strokes, heart disease, lung cancer and chronic respiratory diseases are the most common ailments caused or aggravated by air pollution. Worldwide, ambient air pollution causes 4.2 million deaths each year, which contributes to 7.6% of all deaths (World Health Organisation, 2016). China has suffered from air pollution due to the rapid development of heavy industries. The estimated mortality due to air pollution related diseases is 1.2 million in 2017 (Institute for Health Metrics and Evaluation, 2019). In 2013, heavy smog started to appear in some major cities in China, causing terrible effects on people's health and commuting (Sun et al., 2016). These events were widely discussed on social media, with people being extremely concerned about their health (Jin et al., 2016).

Although the Chinese government has implemented a series of stringent policies to combat air pollution, the heavy reliance on non-clean primary energy (e.g., coal) suggests that the implementation of further air pollution reduction policies may harm the country's economic growth. Therefore, as a developing country, its government needs to consider the trade-off between economic growth and air quality improvement. Given the current strict air pollution policies and much-improved air quality, the government may opt for reduced implementation to maintain economic growth, which implies that the air quality may deteriorate. Benefit measures for air quality improvement can assist policy-making, and a number of studies have been conducted to elicit people's preferences for air pollution reduction in China using either secondary data or surveys, yet literature on the valuation of air quality benefits when both improvement and deterioration scenarios could occur is scant. In addition, as human's understanding of nature is incomplete, uncertainty around the environmental policy outcomes is highly likely to occur, yet most policy outcomes are specified as certain in the literature of environmental economic valuation.

The key research aim of this thesis is to elicit people's preferences and welfare estimates in a context where the change of air pollution policy could cause both improved and deteriorated air quality using discrete choice experiments (DCEs). In addition, policy outcomes are described as probabilistic in two DCEs to reflect that there is a likelihood that the outcome will occur. Based on this framework, three specific issues are investigated: Firstly, previous findings suggest that respondents react more strongly to losses than gains relative to their reference points (Kahneman and Tversky, 1979). In Chapter 2, I investigate whether this phenomenon exists in environmental decision making. The next topic is to explore whether different beliefs about collective action on air quality improvement and views about compliance with social norms are associated with preferences towards air quality changes. Secondly, in Chapter 3, I investigate possible behavioural rules respondents apply in risky decision making when the policy outcomes of air quality are specified as uncertain. Lastly, Chapter 4 explores whether a risky choice framing in the DCE affects individuals' environmental decision making, using a split-sample design.

The remainder of Chapter 1 is structured as follows: Section 1.1 provides a detailed introduction to the issue of air pollution in China, existing policy measures regarding the issue and the importance of measuring the benefits of air quality improvement. Section 1.2 briefly introduces benefit estimation for environmental goods, common economic valuation methods applied in environmental evaluation, and the economic theory underpinning DCE. Section 1.3 states the research questions, methodology and contributions of Chapter 2-4.[1]

1.1 Study context: Benefit measures for clean air

1.1.1 Air pollution and its effects on wellbeing

Outdoor air pollution is one of the most severe environmental risks to a human being's health, and contributes to more deaths than other common risks such as malnutrition, alcohol abuse (IHME, 2015). In 2016, over 90% of the world population lived in places where the air quality does not meet the safe standards set by the World Health Organisation (WHO) (WHO, 2016). The estimated number of premature deaths due to outdoor air pollution is over four million, causing a one-year loss of life expectancy, and those living in developing countries and the elderly are much more vulnerable to ambient air pollution (WHO, 2016; IHME, 2015).

One of the main impacts of air pollution on human wellbeing is the health effect. Long exposure to heavy air pollution is reported to be linked to strokes, lung cancer, heart disease and other respiratory diseases (IHME, 2015). For example, 41% of deaths from chronic obstructive pulmonary disease, 19% of deaths from lung cancer, 16% of deaths from ischemic heart disease and 11% of deaths from strokes are caused by air pollution (IHME, 2015). Research also finds that air pollution causes non-trivial effects to one's mental health (e.g., psychiatric disorders) in the U.S. and Denmark (Khan, 2019). There is also evidence that long term exposure to air with high particulate matter (PM) concentrations leads to olfactory dysfunction (see Ajmani et al. (2016) for a literature review). Additionally, outdoor air pollution can affect transportation through bad visibility, which can cause flight cancellations,

[1] For Chapters 2–4, I initiated the research projects, collected the data and conducted the analysis, whilst my supervisors Emmanouil Mentzakis and Marije Schaafsma have provided precious comments to improve the quality of the research at different stages of the thesis.

traffic jams and accidents. Other impacts include crop losses (Tai and Martin, 2017) and school closures (Sun et al., 2016).

According to the WHO, the main air pollutants include particulate matter smaller than 10 and 2.5 microns in diameter (i.e., PM2.5/PM10), nitrogen oxides, sulphur dioxide and ground-level ozone, with each originating from different sources. For example, particulate matter mainly comes from car emissions, solid-fuel burning (e.g., coal burning) and industrial activities such as building construction and mining. Nitrogen oxides and sulphur dioxide come from industrial burning and vehicle emissions, and ground-level ozone, a pollutant that has only gained more attention for its health impact recently, is generated when high-level nitrogen oxides and volatile organic compounds are irradiated by sunlight. In particular, the detrimental health impacts related to PM10 and PM2.5 are stressed, as these pollutants are small enough to penetrate lung passageways and enter the bloodstream with the possibility of causing cardiovascular diseases (WHO, 2016).

In modern history, some cities have suffered from heavy smog events, causing large mortality numbers and massive economic losses. The great smog of London that happened in the winter of 1952 is one of the most famous events. Visibility was reduced due to a thick layer of pollutants formed above the city because of coal burning, and more importantly, the smog caused about 4,000 deaths and 25,000 cases of sickness during that winter, according to the Meteorological Office. This striking event caused the government to introduce the first Clean Air Act in the U.K. in 1956, which aimed to significantly reduce domestic air pollution by setting up smoke control zones, insisting on the use of pollution control appliances by heavy industries and shifting to cleaner forms of energy use and production. In the U.S., New York City and Los Angeles were reported to have experienced heavy smog during the middle of the last century, causing various health problems among their citizens. In the early 1960s, the United States Congress enacted the Clean Air Act to set emission limits and standards of various pollutants for the transportation and heavy industries, with its subsequent amendments in the 1970s and 1990s imposing stronger restrictions on polluting emissions. According to the Environmental Protection Agency, a significant drop in air pollution related mortality rates was seen by the end of 2010, due to the act (Environmental Protection Agency, 2019).

1.1.2 Air pollution in China

1.1.2.1 The effects of air pollution and governmental action in China

Ever since the process of industrialisation and urbanisation began decades ago, China has been suffering from air pollution. Matus et al. (2012) has estimated that the economic cost of air pollution in 2005 was about 112 billion Chinese RMB, equivalent to 5% of the country’s annual GDP. In the northern part of China, air pollution in 1980 – 2000 caused a two-year reduction in life expectancy

(Chen, Ebenstein, et al., 2013). Recent data show that air pollution caused 1.2 million premature deaths in 2017 (Health Effects Institute, 2019).

In 1973, an initial plan for environmental protection was proposed, in which the issue of air pollution was first mentioned. This plan was later legislated as Law of Environmental Protection in 1979 (and amended in 2014 when more stringent standards were set). Emission standards for different air pollutants were subsequently set to regulate heavy polluting industries, during which the emphases were placed on sulphur dioxide and total suspended particulates, two pollutants were mostly linked to industrial emission from China's rapidly-developing secondary industries. One of the famous implementations is the set-up of Two-Control-Zone in 2000, within which specific limits on sulphur dioxide concentrations were set in order to reduce acid rains (Hao et al., 2000). However, due to the low cost of law breaking, a lack of incentives in local government and a poor monitoring capacity, those policies were barely effective (Wang, 2006).

In 2006, air pollution first entered China's 11th *Five-Year-Plan* framework (2006-2010), in which projects on air quality improvement were raised to the status of national goals and were to be mandatorily achieved with detailed quantitative targets (Jin et al., 2016). The tasks related to these targets were allocated to each province in China, and the results of those tasks were associated with the promotion of the main leaders in each province. These measures aimed at incentivizing the local governments to participate seriously in air quality management (Schreifels, 2012). Higher and detailed standards were set for vehicle and industrial emissions, subsidies were provided by the governments to phase out coal-intensive industries and transfer to cleaner energy use. However, the overall improvement of air pollution in China was not significant. Some local governments were found manipulating emission data (see Ghanem and Zhang, 2014), although the problem was reported to be mitigated after the central government participated in data verification (Song, 2015). Additionally, pollution abatement was mainly focused on sulphur dioxide and nitrogen dioxide, whilst the detrimental effects of secondary pollutants, for example PM2.5 and PM10, were not well-highlighted (Jin et al., 2016). Another reason for the insignificant improvement is that targets were heterogeneous across provinces. Industrial-intensive provinces were having considerable difficulties in meeting the targets, as resources that could be used for combating the pollution issue were limited (Wu et al., 2015). Interestingly, the significant drop in air pollution during the Olympics held in Beijing in 2008 provides a successful example of air pollution reduction. Strict pollution controls were imposed on polluting industries, transportation and construction site in Beijing and its neighbouring regions (e.g., Tianjin, Hebei, Shaanxi and Inner Mongolia) (Zhang et al., 2008). The pollution dropped remarkably, but the beneficial effect vanished not long after the Olympics (Chen, Jin, et al., 2013).

The year 2013 was another milestone in tackling air pollution; it was during this year that a severe haze occurred in some major cities that had exceedingly high concentrations of PM2.5. The event was subsequently widely discussed in social media, causing public panic (Jin et al., 2016). The central government then enacted the China National Action Plan on Air Pollution Prevention and Control, a plan that articulated detailed quantitative targets to reduce PM2.5 and PM10. PM2.5 was also formally included as one of the indicators to be monitored. Detailed measures include updating emission standards, setting a coal consumption cap, providing subsidies for the individual and public use of eco-friendly energy and providing funding for the construction of pollution monitoring networks. A large amount of investment has been made by the Chinese government on air pollution reduction projects. According to the China Council for International Cooperation on Environment and Development, the Chinese Premier stated that the central government had spent approximately 255.5 billion RMB (£27.86 billion) in 2018 on air pollution policies (China Council for International Cooperation on Environment and Development, 2019). As one of the cities where the most stringent pollution policies were imposed, Beijing alone has spent 80 billion RMB (£8.72 billion) on air pollution controls (Zhang et al., 2019). With words such as *Declaration of War against Pollution*, the Chinese government has demonstrated its political will to strengthen the air pollution controls within clear time limits (Jin et al., 2016). By the end of 2017, the levels of several main air pollutants have been decreased, with some being reduced massively (see Table 1.1).

Table 1.1 Annual average pollution levels in Beijing by the end of 2017 and corresponding pollution standards set by China and WHO

Main air pollutants (ug/m^3)	**Beijing** [b]	**National standards**		**WHO standards**
		Grade I	Grade II	
SO_2	8	20	60	20 [c]
NO_2	46	40	40	40
$PM_{2.5}$	57	15	35	10
PM_{10}	84	40	70	20
O_3 [a]	99	100	160	100

Notes: (a) Unit: maximum daily 8 hours mean. (b) Data come from a real-time air quality tracking website https://www.aqistudy.cn (in Chinese). (c) Unit: maximum daily 24 hours mean.

At the country level, sulphur dioxide and nitrogen dioxide decreased by approximately 50%, mainly due to higher energy efficiency and more strict traffic bans (Zeng et al., 2019). PM2.5 and PM10 decreased by 41.9% and 29.1% respectively in 31 provincial capital cities or municipalities in China, yet ground level ozone was increased considerably (Zeng et al., 2019). Beijing, the capital of China, has been suffering from haze for a long time, and motor vehicles are the main contributor to the local emissions. The local authority has implemented a series of policies, including new vehicle controls, driving restrictions on private cars, subsidies for green vehicles and setting higher fuel quality standards. In Beijing, it is believed that smog is transported from those neighbouring cities where heavy industries are centralized. Therefore, the central government set up an air pollution control zone covering Beijing, Tianjin, Hebei, within which unified plans and coordination mechanisms were established in order to jointly combat the heavy air pollution (UN Environment, 2019). As a result, the ambient concentrations of SO2, CO, NO2, PM2.5 and PM10 in Beijing fell by 70.4%, 38.2%, 17.9%, 35.6% and 22.2% respectively from 2013 to 2017 (UN Environment, 2019). However, as can be seen from Table 1.1, although some pollutants have been reduced to the levels below the standards set by the Chinese government, PM2.5 and PM10 still exceeded the Grade II standards, and are much higher than the WHO standards. The results of Air Quality Index (AQI), which is a composite air quality measure, showed that Beijing's AQI dropped to 98 in 2017 (Wang, 2020), situated within the "Good" category (see Table 1.2).

Table 1.2 Classification of the AQI and corresponding degree of pollution

AQI	Classification	Description
0-50	Excellent	Air quality is good for everyone
51-100	Good	Only very few sensitive people should reduce outdoor activities
101-150	Lightly polluted	Sensitive groups should reduce outdoor activities
151-200	Moderately polluted	Sensitive groups should avoid outdoor activities and general population should reduce outdoor activities
201-300	Heavily polluted	
301-500	Severely polluted	All people should avoid outdoor activities

Note: Classification is based on the classification used by China's Ministry of Environmental Protection.

1.1.3 The dilemma of economic growth or air quality improvement

The performance of economic growth of a local area was the indicator that is closely related to the promotion of local leaders, before the green indicator was included as part of the governance assessment (Jia, 2017). Environmental targets were included and emphasized as part of the assessment system of local authorities, when the central government proposed an Environmental Protection Inspection Programme in 2015, following the PM2.5 crisis that occurred in 2013. The programme stated that an inspection team would be formed by the central government to supervise pollution reduction implementation in local areas, especially places where heavy air pollution occurred. The team investigated all 31 provinces in China between 2016 and 2017, with more than 17,000 local officials being questioned and punished to different extents for failing to achieve the pollution management targets set by the central government (Wu and Hu, 2019). Since then, local governments have been incentivized to seriously consider environmental management alongside economic growth.

However, the conflicts between economic growth and air quality improvement in China still exist at both national and local levels, and despite its political will in air pollution management, the government has an incentive to make a trade-off between economic growth and air quality improvement. From the perspective of the local authority, the incentive mechanism of the promotion system still leads to the prioritization of economic development, even if environmental management is part of the assessment. This is because economic accomplishments such as GDP growth and job creation can be seen easily within a 5-year appointment period of a city mayor, whilst the benefits of environmental improvement cannot be evaluated in such a short term (Jia, 2017).

At national level, China's energy consumption is still heavily reliant on the coal industry. As can be seen from Figure 1.1, according to the BP Statistical Review, coal accounted for 58% of the primary energy consumption in China in 2018, while renewable energy such as solar, wind, biomass and geothermal only accounted for 4.4% of the total energy consumption (BP, 2019). In winter, air pollution spreads across most cities in northern China due to central heating system, for which coal is the main fuel. In 2017, the central government initiated an energy use transformation plan called Coal-to-Gas, a gasification campaign that aimed at switching from coal consumption to natural gas. Gas is assumed to be a cleaner alternative as it produces fewer air pollutants than coal. The policy was considered to be aggressive as it quickly increased the demand for gas, leading to shortages in the gas supply (Miyamoto and Ishiguro, 2018). In regional areas where small scale coal burning was banned, numerous homes and schools were left without proper heating (Lian et al., 2017; Hornby and Zhang, 2017, Dec. 4). Therefore, many provinces suspended or cancelled the implementation of the plan due to gas shortages and unaffordable gas price (Jin et al., 2016). For example, the local government in Beijing was reported to have restarted using coal in heating provision (Hornby and Zhang, 2017, Dec. 7).

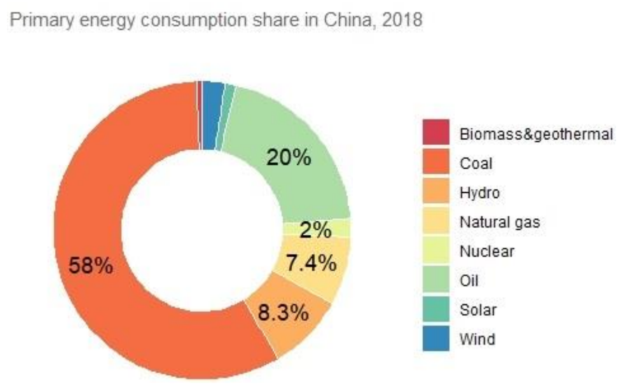

Figure 1.1 Primary energy consumption in China by fuel, 2018

As the plan was proved not being feasible, at least in the short term, the National Energy Administration subsequently softened its stance and allowed cities to choose the most accessible form of energy in central heating (Yep and Liang , 2019).

Another proof of the government's consideration of the economy-air quality balance can be found in the goals of the Three-year Action Plan set by the central government in 2018. The plan expanded targeted areas, but loosened the standards of air pollution reduction. Cities were required to reduce PM2.5 by a further 18% by the end of 2020, compared with the levels in 2015, yet over 20% of the targeted cities had already met this target by the end of 2017 (Hao, 2018). For example, the PM2.5 concentration in Beijing was 58ug/m3 by the end of 2017, whilst the target in the Three-year Action Plan is no more than 65.2ug/m3 by the end of 2020 (details are shown in Figure 1.2, and the data is from (Hao, 2018). This implies that there was room for those cities to adjust their current air pollution implementation based on their policy prioritization, and the local governments in those areas where rigorous pollution controls were implemented, may choose to relax their current air pollution policies to maintain economic growth, which may cause the local air quality to deteriorate.

Figure 1.2 Annual mean PM2.5 levels and the targets in Beijing

1.2 Economic valuation and welfare estimates

1.2.1 Economic valuation

In order to know whether the high expenses on air quality measures of the Chinese government are sufficient to cover the societal benefits obtained from these pollution reduction projects, research in measuring the economic value of air quality improvement is needed.

Economic valuation is an important method that is used to inform rational decision making of individuals and organisations in society. Monetary values are assigned to goods or services based on people’s willingness to pay for obtaining the benefits of the goods or services. For goods where a market already exists, equilibrium prices based on market supply and demand are often seen as the most appropriate indicator of their economic value. The government is able to maintain the efficiency of the distribution of the goods and services by adjusting the prices, and thus mitigate the possibility of market failure. However, most environmental goods and services do not have market prices reflecting their true values, in which case this market failure will affect the efficiency and equality of non-market goods. Additionally, many environmental goods, such as clean water, air and forest, are public goods. Free-riding may occur for such public goods, when people enjoy the benefits of common resources without paying for them, causing negative externalities to the rest of society. Examples include overfishing in a pond that belongs to a community, or deterioration of residents’ health conditions due to local air pollution.

From the point of view of policy makers, appropriate policy decisions can be made and implemented to address the issue using cost-benefit analysis, a method that aims to evaluate the effectiveness of a policy based on judgement of costs and benefits of the policy. This method has been widely applied in environmental policy evaluations in a number of countries (Zhang et al., 2019). Economic valuation of environmental goods and services helps to provide information about the social benefits of the goods. Such information serves a purpose of providing prices for non-market products, and hence the inclusion of the value of these products in policy-making.

Economic valuation has helped to provide evidence-based policy implications and assisted environmental decision-making in the UK, including the design of an environmental tax and policies prioritisation. Research that measure monetary valuation of different environmental goods and services is often funded by the UK governmental agencies. For example, DEFRA has used evidence from economic valuation to inform policies in ecosystem conservation, air quality and natural hazard defence (Atkinson et al., 2018). Other governmental bodies are the Environment Agency, Department for Transport, Local Government and the Regions, and so on. Many international and regional agencies, for instance, the United Nations Environment Programme and Directorate-General for Environment also rely on economic valuation to provide policy advice in environmental management (Gómez-Baggethun and Ruiz-Pérez, 2011).

In China, although the awareness and practices of systematic economic valuation of environmental impacts are lagging behind those of developed countries, recent legislation regarding environmental protection emphasizes the importance of economic valuation in policy and project management (Lindhjem et al., 2007; Khan and Chang, 2018). According to the Chinese Environmental Protection Law (first enacted in 1989 and revised in 2014) and the Environmental Impact Assessment Law (first enacted in 2002 and revised in 2014), a certificate of environmental impact assessment should be obtained before conducting any construction projects in China, and the economic valuation of the environmental impacts of the construction projects and the corresponding mitigation measures must be included in the environmental impact assessment.

1.2.2 Willingness-to-pay, Willingness-to-accept and Hicksian welfare measures

Monetary values of environmental goods or services are often measured by willingness-to-pay (WTP) and willingness-to-accept (WTA). WTP measures the maximum amount a consumer wants to pay for a good/service, whilst WTA means the minimum amount she will accept as compensation for a change of that good/service (Freeman, et al., 2014); both indicators are closely related to the foundations of welfare economics. For instance, suppose an individual can choose to consume either an environmental or a private good under the framework of utility maximization. To maintain the good at the same utility level, the maximum amount of a private good one has to give up (i.e., WTP) for an increase in the quantity of an environmental good, is called compensating variation. Another welfare measure is called equivalent variation, which describes the minimum amount of private goods used as compensation if the increased consumption of the environmental goods does not occur. However, if the reference level changes and the situation is conditional on a decrease of consumption for environmental goods, then WTP (WTA) can also be used to describe equivalent variation (compensating variation). Table 1.3 describes the relationship between Hicksian welfare measures and WTP/WTA, which depends on how the reference level is framed.

Table 1.3 Relationship between Hicksian welfare measures and WTP/WTA

Scenarios	**Compensating Variation**	**Equivalent Variation**
Environmental improvement	WTP for an environmental improvement that occurs	WTA for an improvement that does not occur
Environmental deterioration	WTA for an environmental deterioration that occurs	WTP to avoid an environmental deterioration

1.2.3 Preference elicitation: stated preference methods

Economic non-market valuation methods can be broadly classified into revealed preference (RP) and stated preference (SP) methods. Generally speaking, revealed preference methods analyse observations of environmental goods consumption directly through real market transactions, whilst stated preference methods rely on decision-making in hypothetical contexts or scenarios (Louviere et al., 2000). In economic valuation of environmental goods, RP method is usually applied to elicit use values, which refer to goods that are actually used by people, for example, the value of a national park or conservation land. Use values can also be option values, referring to values of goods that are not used currently, but might be used in the future. Individuals may also pay for the environmental goods for reasons of altruism, bequests to future generations or merely for the existence of the goods, and these values are part of the non-use values (Bateman et al., 2002). SP method is more commonly-used when a non-use value is an important part of the good under valuation, or where a new feature of the good has just been introduced and no revealed preference data can be used. In the case of air quality improvement, SP method allows researchers to elicit benefits of altruistic values in addition to the pure health benefits for individuals themselves, serving as a complement in benefit measuring approaches for clean air (although from a purely egotistical perspective, altruistic preferences can be internalized into one’s own utility function). For example, people may want to pay to avoid air pollution related effects for their children, other family members and even other members of the society, in addition to the benefits for themselves.

RP data is obtained through market observations that reveal people's real consumption behaviour, whilst SP data reflects individuals' decisions in hypothetical context. This hypothetical nature has given rise to a number of criticism (Cummings et al., 1995; List and Gallet, 2001; Murphy et al., 2005). In a hypothetical scenario, WTP may be overestimated due to the lack of incentive compatibility. In other words, respondents tend to over-state their WTP in contexts where actual payments are not needed. Therefore, the external validity of the results obtained from the SP methods is doubted.

Although the SP methods have been criticized for a long time for its lack of validity, there are a number of reasons why this method is still being applied in environmental economics. First, the SP methods estimate the demand for new environmental goods/services that do not have a market or close substitutes (Louviere et al., 2000). Given the values of the environment and its resources, environmental economists aim to find the best allocation of those environmental resources in a competitive market that maximises the welfare of the society. Therefore, the estimation of demand is important to guide policy-making when market behaviour is non-existent. Second, although demand for some environmental goods can be inferred from other goods in the market using the RP methods, RP estimates may be seriously biased if there is no variability in the quantity of the environmental good, in which case the value of the environmental good is not reflected in market. For example, the house price may not effectively reflect the demand for clean air based on hedonic price method (a type of RP methods), if the air pollution level changes little in an area. Finally, the choice of functional forms and misspecification of control variables have long been challenges in research using the RP methods (Chau and Chin, 2003), whilst these issues are minimized in a SP context with a proper experimental design.

1.2.3.1 Contingent valuation method

A common SP elicitation method is contingent valuation method (CVM). Respondents are asked to state their maximum WTP/minimum WTA for a change of provision of an environmental good or service in a hypothetical scenario designed by researchers. The aims of CVM are the followings: (a) to infer benefits of the environmental goods for the whole population from WTPs of the chosen sample. (b) linking WTPs with individual characteristics (e.g., demographic and socio-economic characteristics, and knowledge and attitudes about the environment), in order to inform the distributions of the WTPs across different social groups (Bateman et al., 2002). A typical open-ended question of CVM is "would you be willing to pay £X for an improvement of air quality in city Y from level a to level b?" In a bidding game format, the above question is repeatedly asked with an increment on the monetary amount if the respondent answers “yes” in the previous questions. The maximum WTP is elicited until the respondent answers “no”. The straightforward open-ended format may lead to large non-response rates and protest answers (Mitchell and Carson, 2013), and the bidding game format suffers from anchoring effects (Green et al., 1998). The anchoring effects (i.e., starting point bias) can be avoided in payment card elicitation format, in which respondents are presented with a range of monetary amounts and asked to state their maximum WTP for a given improvement of an environmental good (Bateman et al., 2002). In a double-bounded dichotomous choice format, an initial monetary bid is proposed and respondents need to accept or reject this bid. A subsequent higher (lower) bid is proposed if the respondents accept (reject) the previous bid. This method can obtain more information, and is thus more statistical efficient than a single-bounded dichotomous choice format in which no subsequent bid is proposed (Kanninen, 1993).

CVM has been applied to estimate the values of different environmental goods, for example, renewable energy (see Stigka et al. (2014) for a literature review) and forest conservation (see Barrio and Loureiro (2010) for a literature review) in both developing and developed countries. However, despite its wide application, results from CVM studies (also from studies using other SP methods) have been criticized by some economists for the acquiescence bias (Hanley et al., 1998) (i.e., people are more likely to answer “yes” than “no” in a survey question regardless of the context) and the sensitivity-to-scope problem (Hausman, 2012).

The National Oceanic and Atmospheric Administration panel proposed guidelines to ensure that CVM practitioners conduct this method properly (Arrow et al., 1993). The report provides suggestions on the selection of survey and preference elicitation formats, on the description of context scenarios and on additional reminders to mitigate different types of bias (Arrow et al., 1993).

1.2.3.2 Discrete choice experiments

The discrete choice experiment (DCE) method has been increasingly applied in environmental studies since the year 2000 (Hanley et al., 2002). The method assumes that any environmental good can be decomposed to different attributes (i.e., characteristics). For example, the value of a conservation area can be described as a combination of values of species diversity, recreation and environmental protection (e.g., the protection of water quality). During the experiment, respondents are presented with a series of choice cards, with each choice card having at least two policy options. In each card, respondents need to choose their preferred policy option from all presented options. As mentioned previously, each hypothetical policy consists of several pre-defined attributes related to the estimated environmental good, with the level of each attribute varying in different policy options. Respondents are expected to make trade-offs between attributes in decision making, from which process the

WTP/WTA estimates can be obtained by the ratio of an environmental attribute to a cost attribute. Some variations of the DCE method, for example best-worst scaling and conjoint analysis, ask respondents to rate or rank part of or all the options in the choice set, instead of simply choosing the preferred one.

Compared with CVM, the choice-based DCE mimics everyday decision making more closely and avoids the acquiescence bias (Adamowicz, 1995). Additionally, as the preferences of respondents are elicited based on scenario changes in a range of levels instead of a single change between two levels, DCE also, to some extent, mitigates the sensitivity-to-scope problem that occurs in CVM (Carson and Czajkowski, 2014). Furthermore, from a policy perspective, policy-makers may be more interested in preference weights of attributes of an environmental good, rather than the good as a whole (Hanley et al., 1998). However, DCE questions can be more complex than CVM questions, which might cause additional cognitive burden on respondents. Furthermore, like other SP methods, as the constructed scenarios in DCEs are hypothetical, the external validity of the obtained WTP estimates may be problematic. To guide SP practitioners, the Association of Environmental and Resource Economists produced a comprehensive guidance for the users of the SP methods, in which several recommendations on designing and practicing DCEs and CVMs are put forward, based on a large corpus of peer-reviewed literature (Johnston et al., 2017).

1.2.3.3 Lancaster's theory and random utility theory

The Lancaster's theory of demand posits that demand for a good can be seen as a demand for the inherent characteristics of that good (Lancaster, 1966). In other words, the overall value of a good can be described as the aggregated values of different characteristics of that good (Ryan, 2004). Lancaster (1966) also emphasizes that attributes that are used to describe characteristics of a good may not be unique to that good. For example, a health attribute in the demand for clean air is also applicable to the demand for clean water. These assumptions underpin the discrete choice experiment method as theoretical foundations in alternatives and choice sets development.

The utility of consumption cannot be observed, but can be inferred from observable consumption behaviour, either in real or hypothetical transactions through random utility maximization (RUM). RUM is systematically developed by Daniel McFadden (McFadden, 1974, 1986), which is then used as an important theoretical foundation of discrete choice experiments. It states that the utility (U_{ni} as stated in equation 1.1) of an individual n choosing a specific environmental scenario i in a bundle of choices contains a systematic part (denoted by V_{ni}) and a stochastic part (denoted by ε_{ni}). The systematic part is usually measured by a linear aggregation of observed characteristics or attributes (X_{ni}) of an environmental good, as described in Lancaster's demand theory, whilst the stochastic part accommodates the non-observable factors and measurement errors that affect an individual's choices. β_k is the estimated parameter *k* associated with the corresponding attribute, representing the weight that respondents place on the attribute of the environmental good. These are described by Equation 1.1.

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \sum_{k=1}^{k} \beta_k X_{nik} + \varepsilon_{ni} \tag{1.1}$$

RUM suggests that choices can only be modelled by the probabilistic utility function due to the existence of the random utility, and a utility maximiser chooses a specific option *i* only when the utility gained from choosing the option is higher than that derived from an alternative option, say option *j*, among all the available alternatives in the given choice set. This is described in Equation 1.2.

$$P(U_{ni} > U_{nj}) = P[(V_{ni} > V_{nj}) > (\varepsilon_{ni} > \varepsilon_{nj})] \tag{1.2}$$

The equation implies that the probability of choosing one option is higher than the alternative option if the utility gained from the former choice is higher than that of the latter one. The unconditional probability of respondent *n* choosing alternative *i* is stated in Equation 1.3.

$$P_{ni} = \frac{\exp(V_{ni})}{\sum_{j=1}^{J} \exp(V_{nj})} = \frac{\exp(\beta_n X_{ni})}{\sum_{j=1}^{J} \exp(\beta_{nj} X_{nj})} \tag{1.3}$$

The error term (ε_{ni}) is commonly assumed to be independent and identically distributed (i.e., no cross-correlated alternatives) following a Gumbel distribution, with its variance being $\pi^2/6$. The welfare measure of interest, namely the WTP of an environmental attribute, can be calculated from the ratio of the estimated coefficient of the environmental attribute to that of a monetary attribute. The calculation process is presented in Equation 1.4.

$$WTP = \beta_e / \beta_c \tag{1.4}$$

where β_e and β_c represent the coefficient of the environmental attribute and monetary attribute, respectively.

Note that in discrete choice modelling, the maximum likelihood estimation is commonly used in obtaining the choice probability that maximises the likelihood function. The likelihood function is expressed in Equation 1.5.

$$L(\beta) = \prod_{n=1}^{N} (P_{ni}(\beta)) \tag{1.5}$$

To facilitate the calculation of derivatives, a log transformation is applied on both sides of the equation, and the log likelihood function is shown in Equation 1.6.

$$Ln(L(\beta)) = \sum_{n=1}^{N} \ln\left(P_{ni}(\beta)\right) \tag{1.6}$$

where ln (·) represent the logarithm function.

1.3 Key research questions, methodology and contributions

Given the serious condition of air pollution in China, economic valuation of the impacts of air quality policies is needed to assist policy-making. In the absence of existing markets for environmental goods, such as air quality, SP data from surveys and experiments where hypothetical markets are constructed can provide preference and monetary estimates of the benefits of clean air.

Several SP studies have provided WTP estimates for air quality in China, (Wang et al., 2006; Istamto et al., 2014; Tang and Zhang, 2015; Wang et al., 2015; Sun et al. 2016; Wang et al., 2016; Wei and Wu 2017; Huang et al., 2018). These studies also investigate the co-benefits[2] and the distribution of the benefits across social groups with different individual characteristics, political views and environmental attitudes. These studies provide evidence-based welfare estimates of air quality improvement for policymaking.

As mentioned in Section 1.1.3, China's primary energy consumption is still dominated by coal, and stringent actions, such as closing polluting factories or banning coal use for heating and cooking, may harm economic growth and related benefits for citizens. Both central and local governments may need to make a trade-off between economic growth and air quality improvement. Some potential actions that prioritize economic growth may imply that air pollution could deteriorate, compared with the current situation. SP literature provides little evidence of individuals' disutility when there is a possibility of air quality deterioration in the near future. The social costs of decreasing the air quality is almost unknown to policy-makers. If citizens are against air quality deterioration and do not consider economic goals as more important, this might affect the legitimacy of governmental actions towards (economic) growth that is associated with further pollution.

[2] In other words, side-benefits, e.g., in addition to improved health, improved visibility is a side-benefit of air quality improvement.

It has been found in the literature that benefit loss due to environmental degradation cannot be simply inferred from benefit gain of a same-sized environmental improvement, which is sometimes called the WTA-WTP gap. The WTP and WTA for a same-sized change of an environmental good should be equal under the neoclassical economic assumptions, yet many empirical SP applications have found a significant WTA-WTP gap for different environmental goods (Mansfield, 1999; Horowitz and McConnell, 2000; Lanz et al., 2009). Loss aversion from prospect theory is one of the most popular explanations for the difference in WTP and WTA. Loss aversion states that people place more weight on monetary losses than on same-sized monetary gains, relative to a reference point (e.g., their current level of wealth) (Kahneman and Tversky, 1979). In a similar fashion for environmental goods, the asymmetry may occur when people weigh the benefit loss from air quality deterioration more than the benefit gain from air quality improvement. This implies that an assumption of equal benefit change under environmental gain and loss may lead to biased welfare estimates (Hess et al., 2008). Therefore, given this context, valid benefit measurement needs to account for scenarios under both air quality improvement and deterioration.

This thesis contributes to the literature on welfare and preference estimates elicitation for air quality in Beijing using DCEs, based on a unique gain-loss framework where preferences for air quality improvement and deterioration are simultaneously estimated. To the author's best knowledge, no SP study has been done to elicit preferences for clean air, based on this framework in China. [3] The welfare and preference estimates elicited from this thesis could be used to guide policy-making in China when trade-offs between economic growth and air quality improvement need to be considered. Specifically, the evidence can be used in policymaking for the final stage of the Three-year Action Plan (2018-2020) and 13th Five-year Plan (2016-2020), and the upcoming 14th Five-year Plan (2021-2025).

Based on this unique framework, this thesis explores different issues using three DCEs of varied design. Three attributes are included in the DCE of Chapter 2, namely health, visibility and bill payment, representing the effects of air quality on individuals' wellbeing and the policy cost for each hypothetical policy option. In each choice card, respondents are presented with three policy options: a status-quo option, which describes a policy that allows the air quality management plan to maintain at the current levels, and two alternative policies with either improved or deteriorated levels in attributes.

[3] Sergi et al. (2019) elicited individuals' preferences for both increase and decrease of sulphur dioxide using DCE. However, from a policy perspective, sulphur dioxide is only considered to be one of the main air pollutants, yet PM2.5 and PM10, the most harmful pollutants causing public panic since 2013 has not been included in their design. Therefore, the generalisability of the welfare estimates from their study is limited.

The first aim of Chapter 2 is to investigate the presence of loss aversion for air quality attributes. Different from traditional DCE design where attributes only move towards a positive direction (i.e., improvements in environmental outcomes), the design in Chapter 2 allows an attribute to be presented as either a gain or a loss relative to the current attribute level. This feature enables the detection of loss aversion.

The second aim of Chapter 2 is to link social capital with environmental preferences and loss aversion. Social trust and social norms are frequently used as indicators of social capital within a community or society, and have been found to affect individuals' decision for environmental improvement through collective actions and intentions to avoid non-compliance behaviour (Polyzou et al., 2011; Halkos and Jones, 2012; Jones, Clark, and Malesios, 2015). However, whether social capital plays a role in the scenario of environmental degradation is rarely discussed. Moreover, studies have shown that social capital is related to loss aversion through social distance[4] (Polman, 2012; Mengarelli et al., 2014). People who are socially more connected to those in the same community are more likely to be affected by the framing of loss aversion.

Lastly, as an additional analysis, Chapter 2 investigates the role of moral considerations. In the gain-loss DCE design, some policy options propose a bill reduction to compensate the deterioration in (at least one) air quality attributes. In such cases, respondents are asked to trade off environmental deterioration for monetary gain (i.e., bill reduction). This type of trade-off can be perceived as a taboo, as achieving personal gain at the expense of public benefit is often assumed to be morally problematic. If respondents are unwilling to make the taboo trade-off, they may ignore the bill reduction scenarios altogether. In the DCE literature, an increasing number of studies have found that not all attributes are considered by respondents (Scarpa et al., 2009; Campbell et al., 2011; Glenk, Martin-Ortega, et al., 2015), and taboo trade-off aversion is rarely mentioned (Chorus et al., 2018).

Chapter 2 contributes to the literature on the investigation of loss aversion preferences for environmental goods. This chapter also contributes to the SP literature on the relationship between social capital and individuals' preferences for clean air. I hypothesize that social capital, which is a measure of social trust and social norms, positively affects the preferences of respondents for air quality improvement and positively associated with the disutility obtained from air quality deterioration. Furthermore, given the link between loss aversion and social distance, social capital is also hypothesized to positively correlate with loss aversion. Lastly, Chapter 2 contributes to the scant

[4] Social distance means to what extent people can accept and interact with those who are not in the same social groups with them. Social groups can be categorised according to individual characteristics, for example ethnicity, age and gender.

literature on the exploration of the experience of moral difficulty when respondents are explicitly asked to make trade-offs between environmental improvement and monetary gain.

Chapter 3 investigates which behavioural rules respondents apply when environmental outcomes are specified as uncertain. In SP studies, hypothetical environmental policies are often assumed to be certain, whilst in the real world the outcomes are often uncertain due to limited scientific knowledge about the environment and various social and political factors affecting the effectiveness of the governmental policies. Welfare estimates may be biased if uncertainty is not incorporated in the experiment (Rolfe and Windle, 2015). DCE designs that incorporate the risk of outcome delivery are becoming increasingly popular (Roberts et al., 2008; Glenk and Colombo, 2011; Bujosa et al., 2018), yet most applications fail to explore various possible behaviours in risky choices. Glenk and Colombo (2013), and Rolfe and Windle (2015) systematically compared the model performance of various specifications following a range of popular behavioural assumptions under risk. Additionally, in most DCE applications, risk is only incorporated in policies that describe environmental gains, and few of them investigate outcome-related risk perception for both environmental gains and losses. This is an important aspect, as prospect theory finds an asymmetric pattern of risk perception between the gain and the loss domains (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). In other words, individuals are found to be risk averse to monetary gains and risk seeking to monetary losses.

The main contribution of Chapter 3 is that it extends the investigation of outcome-related risk perceptions of environmental policies to both the gain and the loss domains. A risk attribute is embedded in the experiment to represent the probabilities around the health outcomes due to air pollution. The ways in which respondents perceive outcome-related risk are explored under the assumptions of expected utility theory, prospect theory and direct risk aversion, which would each predict different behavioural patterns (as explained in Chapter 3). Furthermore, Chapter 3 provides the first study that investigates asymmetric behavioural rules between the gain and the loss domains using the DCE.

Chapter 4 explores the effects of risky choice framing on individuals' decision making for environmental goods. Different from Chapter 3 in which risk is treated as an independent attribute, this chapter places the information of risk and the associated health outcomes in the same attribute. Some DCE studies investigate the effects of risk by comparing a certain treatment with an uncertain treatment where environmental outcomes are specified as probabilistic (Roberts, et al., 2008; Torres et al., 2017). However, the corresponding expected values of the outcomes for the uncertain treatment would be lower than their certain counterpart. Thus, under the assumption of expected utility theory, the estimated treatment effects include not only the effect of presenting risk, but also the effect of changes in expected outcomes, and hence the claimed finding will be an overestimation of the pure risk effects. Faccioli et al. (2019) present the only DCE study that disentangles the two effects using a split-sample design where the expected outcomes for the certain treatment are equal to those in the uncertain treatment. The estimated treatment effect thus represents the pure effects of presenting risk. Moreover, the perception of risk is also affected by the magnitude of the probability. Prospect theory states that in the monetary gain domain, people are risk averse when the probability is large, and risk seeking when the probability is small, and vice-versa for the monetary loss domain (Tversky and Kahneman, 1992). Few environmental studies have attempted to test probability-specific risk preference, yet for an environmental policy that has multiple outcomes with different probabilities attached, respondents have been found to distort those probabilities (Cameron, 2005; Wibbenmeyer et al., 2013; Hand et al., 2015). Therefore, it is relevant to test whether the effects of risky choice framing mentioned previously would be affected by the magnitude of the probability.

Chapter 4 contributes to the investigation of the effects of risky choice framing by comparing individuals' preferences for pollution-related health outcomes in a certain treatment with those in an uncertain treatment of equal expected outcomes. Another novelty of this chapter is that a small and a large probabilities are used to describe the magnitude of risk, permitting the estimation of probability-specific risk effects. Moreover, expected values of the health outcomes for the uncertain treatment are explicitly presented alongside the probabilities and outcomes, aiming to mitigate the bias due to an inability to accurately calculate expected outcomes.

In the final chapter of this thesis (Chapter 5), I present further discussion regarding the WTP findings in Chapter 2 and the issue of insensitivity to bill reduction. Next, I present policy and research recommendations, limitations of the thesis and a general conclusion.

Chapter 2
Social Capital and Loss Aversion in Discrete Choice Experiment

2.1 Introduction

Air pollution is a well-recognized problem in China, with the pollution levels in cities in eastern and southern China often exceeding the air quality standards set by the Chinese officials. The severe negative effects of air pollution on human health, typically on respiratory system, have caused 350,000-500,000 annual deaths in China, which have triggered public and official concerns (Chen, Wang, et al. 2013).

Central and local governments are developing and implementing stringent air pollution control measures targeting industries and households, which affects citizens' decision making in many aspects of life. In order to inform cost-benefit analyses in the design of policy instruments, individuals' preferences and social welfare estimates (e.g., WTP) for air quality improvement are needed. Stated preference (SP) methods, and in particular discrete choice experiments, have been used to assess individuals' preferences associated with clean air or air quality improvement in China (Tang and Zhang, 2015, Huang et al. 2018; Sergi et al., 2019), as well as other countries and regions (Jara-Díaz and Vergara, 2006; Yoo et al., 2008; Ghorbani et al., 2011; Tekeşin and Ara, 2014).

However, air pollution policies implicitly involve trade-offs between health/environmental benefits and economic growth or household budgets. Governments may opt to sacrifice air quality to maintain economic development or vice versa. Hence, in the framing of choice experiments, policy options that contain both the improvement and deterioration scenarios should be considered. At the same time, gain-loss framing and its effects on behaviour have been demonstrated in experimental studies (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991). In prospect theory, loss aversion posits that respondents attach larger disutility to a monetary loss than utility of a same-sized monetary gain (Kahneman and Tversky, 1979). Furthermore, a pattern of diminishing sensitivity behaviour is often observed, where individuals are more sensitive to changes near a reference point, which translates to a concave individual utility function when the estimated good is specified as a gain, and a convex function when it is specified as a loss.

An increasing number of DCE studies in transportation and environmental economics have investigated asymmetric gain-loss (i.e., loss aversion) preferences (Hess et al., 2008; Bateman et al., 2009; Lanz et al. 2009; Masiero and Hensher, 2010; Glenk, 2011; Aravena et al., 2014; Ahtiainen et al., 2015; Bartczak et al., 2017), yet the results are mixed. Gain-loss asymmetry are not present in all attributes, while evidence for diminishing sensitivity is again present in some (Hess et al, 2008; Lanz et al., 2009; Masiero and Hensher, 2010), but not in other studies (Ahtiainen et al., 2015). Thus, the investigation of gain-loss asymmetry in preferences for air quality serves a dual purpose, namely that of a framing effect recognized in the experimental literature and that of a policy option to be evaluated based on the current dilemma in air quality management in China. Failure to account for gain-loss asymmetry in the DCE design can lead to biased welfare estimation (Hess et al., 2008).

Another issue this study focuses on is the role of social capital in individuals' environmental decisions. Some recent SP studies stress the positive influence of social capital on collective environmental actions (Polyzou et al, 2011; Halkos and Jones, 2012; Jones, Clark, and Malesios, 2015). Social capital is believed to be closely related to social trust and social norms (Putnam, 1993; Pretty, 2003). In environmental decision making, social trust affects individual environmental behaviour through the confidence in collective activities in support of natural protection in a community or society (Wagner and Fernandez-Gimenez, 2008). Social norms affect individuals' utility if there are norms that the action of environmental protection would benefit the community or society (Polyzou et al., 2011). Social norms also relate to individuals' disutility caused by environmental deterioration, as environmental degradation is seen as a deviation from the social norm that public interests of the community should be protected (if such a norm exists in the community or society).

Furthermore, recent literature has suggested that loss aversion is lower in settings where individuals make decisions for others rather than themselves (Polman, 2012; Mengarelli et al., 2014; Zhang et al., 2017). The finding can be theoretically linked to the principal-agent model in economic theory (Ross, 1973; Stiglitz, 1974; Mirrlees, 1999), where an agent is assumed to be less responsible in making choices for her principal than for herself due to conflicted objectives (i.e., when there is inconsistency between maximising her principal's benefit and the benefit of herself). In that case, the agent would be less sensitive to the losses of others than those for herself (Mengarelli et al., 2014). In the meantime, based on evidence from neuroscience and empirical evidence that emotion plays a significant role in the formation of loss aversion (Sokol-Hessner et al., 2013; Campos-Vazquez and Cuilty, 2014; Wang et al., 2014; Charpentier et al., 2016), Polman (2012) and Zhang et al. (2017) find that social distance is negatively related to loss aversion preference. Increased social distance creates reduced emotional attachment to others, and hence people will more likely to be "cold" and less likely to be affected by the effects of loss aversion. Interestingly, since social distance is strongly correlated with various indicators of social capital (Putnam, 2007),[5] a possible link may exist between loss aversion and social capital. People who have higher social capital, which implies lower level of social distance with others, may have higher loss aversion preferences in other-regarding decision making than those who have lower social capital. To sum up, various social capital indicators (i.e., social trust and social norms)

[5] Putnam (2007) states that mutual trust and social networks increase tolerance among people with different social contexts, and thus reduce the social distance between each other in the community. Empirical evidence has also suggested the link between social distance and indicators of social capital (Kobayashi, 2010; Wise and Driskell, 2017), yet the direction of the effects could differ across different types of networks (Côté and Erickson, 2009).

may connect with individuals' environmental preferences, as well as loss aversion preferences for the environment. Figure 2.1 shows how these concepts are linked.

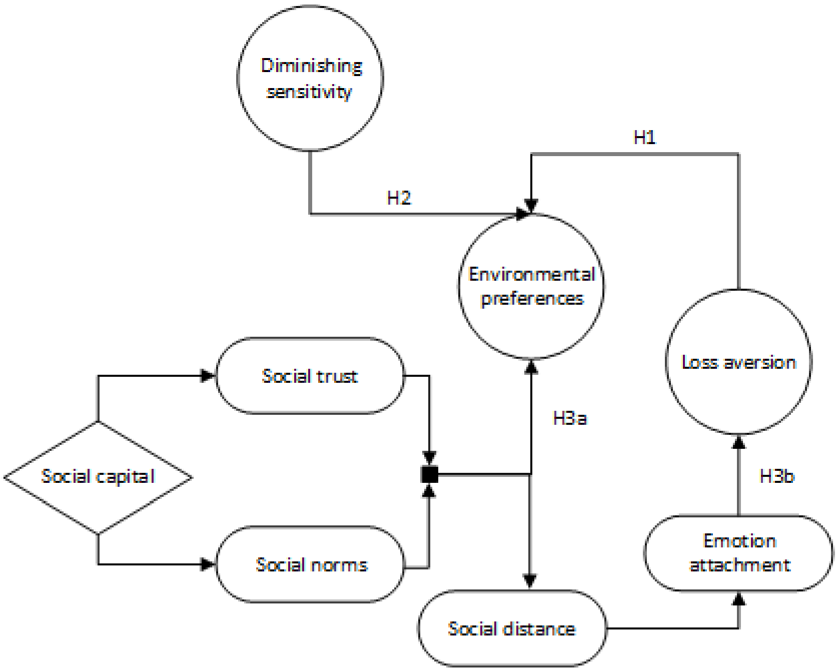

Figure 2.1: Conceptual framework of Chapter 2 [6]

[6] The diamond shape box indicates the initial element, the oval shape boxes indicate the mediators and the round shape boxes indicate the terminal elements. The arrows represent the links between different objects, and the text beside those arrows represent hypotheses to be tested.

This is the first study to examine the effects of social capital on individual preferences for both environmental improvements and deteriorations and on loss aversion using a DCE. These effects are examined in the context of air pollution policies in China using a novel experimental design where gains and losses are separately presented relative to fixed reference points. Attribute levels in the loss domain mirror those in the gain domain, thereby eliminating possible loss aversion manipulation bias (Walasek and Stewart, 2015). It is expected that higher social capital scores are correlated with higher preferences for environmental improvement and higher level of disutility from environmental deterioration. Furthermore, given the connection between social capital and social distance (i.e., higher social capital scores are correlated with lower social distance), higher social capital scores are expected to correlate with larger loss aversion preferences relating to environmental changes.

In this experiment, air quality attributes are allowed to vary in both the gain and loss domains, so that loss aversion can be detected by comparing parameters of attributes from the two domains. Diminishing sensitivity is investigated by testing the non-linear effects in attributes on utility. Heterogeneity of environmental preferences and loss aversion in individual preferences related to social capital are explored, by regressing individual conditional estimates inferred from the corresponding unconditional estimates of mixed logit model on different (individual-level) social capital indicators. Alongside the full sample analysis, k-means clustering method is used to detect respondents with extraordinary loss aversion preferences (i.e., outliers), and the correlation between social capital and loss aversion is retested in a sub-sample where the outliers are excluded.

The results show that loss aversion is present in preferences for both environmental attributes (i.e., a health and a visibility attributes). Diminishing sensitivity behaviour is also found for health improvement and deterioration. Respondents who have higher social capital (i.e., social trust and norms) scores obtain higher level of utility in the scenarios of air quality improvement, but bear higher level of disutility in the scenarios of air quality deterioration. Those with higher social capital scores are found to be significantly more loss averse towards air quality changes in the sub-sample where identified outliers are excluded, but the results are not significant for the full sample.

Furthermore, people are found to be insensitive towards bill reduction in the scenarios of air quality deterioration in preliminary analysis, causing the WTA estimates to be incalculable. One explanation is that moral concern may occur under the gain-loss framework where respondents are asked to obtain monetary compensation at the expense of air quality deterioration. Classic economic theory assumes that individuals are rational and purely self-interested in decision making, yet studies have shown that obtaining monetary gains at the expense of environmental losses is often regarded as a taboo trade-off and could cause moral outrage (Tetlock, 2003; Daw et al., 2015; Stikvoort et al., 2016). Additionally, taboo trade-off may invoke non-compensatory choice heuristic due to environmental ethical consideration (Stevens et al., 1991; Rosenberger et al., 2003; Araña and León, 2009). Given the experimental design of this study where taboo trade-offs exist, it is likely that respondents ignore the scenarios of bill reduction to avoid the moral choice of exchanging environment deterioration for monetary gain. Therefore, apart from the main analysis, I further explore whether attribute non-attendance (ANA) and taboo trade-off aversion preference could explain the lack of sensitivity in bill reduction. Taboo trade-off aversion is incorporated by placing a taboo penalty in utility function, in addition to attribute effects. To test cost non-attendance, this chapter applies a special latent class model where the cost parameter in one class is set to be zero, representing the non-attendance class, whilst parameters in other classes are estimated freely. Results confirm the presence of taboo trade-off aversion and a large proportion of ANA in the cost attribute, implying that moral concern related to the tradability between money and the environment may cause respondents' insensitivity towards bill reduction.

Section 2.2 gives an overview of the relevant stated preference literature. Section 2.3 presents the experimental design and the details of the survey. Section 2.4 explains the modelling framework of this chapter. Section 2.5 presents the results. Section 2.6 discusses the implications of the results and limitations of this chapter, and the conclusion of this chapter is presented in Section 2.7.

2.2 Literature Review

2.2.1 Eliciting willingness-to-pay for air quality

A considerable body of literature has been developed in which stated preferences methods are used to estimate individuals' WTP or WTA (Stephens, 2010). A number of studies has elicited WTP for air quality improvement in different countries or regions using DCEs (Diener et al., 1997; Jara-Díaz and Vergara, 2006; Yoo et al., 2008; Ghorbani et al., 2011; Tekeşin and Ara, 2014; Rizzi et al., 2014; Tang and Zhang, 2015; Huang et al., 2018; Sergi et al., 2019). Most DCE studies include a health attribute, represented by premature deaths, general hospital admissions, or hospital admissions of specific diseases caused by ai pollution (Desvousges et al., 1997). Some include visibility (Diener et al., 1997; Jara-Díaz and Vergara, 2006; Yoo et al., 2008; Ghorbani et al., 2011) or odour (Diener et al., 1997; Ghorbani et al., 2011) as further attributes. Commonly, WTPs for health improvement are larger than those for visibility improvement of similar extent, with the exception of Rizzi et al. (2014) who have found WTP for improved hospital admissions lower than that for improved visibility.

An increasing number of DCEs have been conducted to understand people's preferences for clean air in China. Tang and Zhang (2015) implemented an internet-based DCE in 29 different cities in China to elicit preferences for air quality improvement. Attributes include mortality, days of haze, policy delay and two specific air control policies (i.e., limit transportation or modernise factory pollutant disposal). Results suggest that WTPs are higher than those in CVM studies in China. Huang et al. (2018) elicited WTP for the reduction of risk of mortality and morbidity due to air pollution in Beijing. Their results show that WTP value is significantly higher in scenarios where the proposed payment vehicle is tax reallocation, than that in scenarios where new tax payment is suggested; this shows that respondents are less reluctant to pay new taxes for environmental protection. Yao et al. (2019) investigated individuals' WTP for air quality improvement at multiple air pollution levels. The attributes are the number of days people would like to stay with clean air, and with light, modest, heavy and severe pollution across the year. Results suggest a higher WTP for the reduction of severe pollution days than for the increase of clean air days. Sergi et al. (2019) conducted a DCE on measuring preferences for avoiding climate change and air pollution caused by carbon and sulphur dioxide emissions in ten major cities in China. They also linked the actual air pollution levels in different cities with corresponding estimated WTPs and found that WTPs in more polluted cities were significantly higher than those in less polluted cities, supporting the correlation between the perception of the level of environmental pollution and WTPs.

2.2.2 Gain-loss asymmetry in stated preference studies

Gain-loss asymmetry or loss aversion is a key feature of prospect theory (Kahneman and Tversky, 1979), which posits that people assign higher weights to losses than gains, relative to a reference point. That is, the utility loss due to decreased amounts of a proposed good is higher than the utility gain for the same-sized increase of the good, and this behavioural pattern is also found when choices are riskless (Tversky and Kahneman, 1991). Hess et al. (2008) present the first study on loss aversion behaviour in DCE literature. The unique design, where gain and loss coefficients of the same attributes are separated, enables researchers to compare utility changes in gain and loss relative to the current situations. However, Hess et al. (2008) also acknowledge that not all attributes follow the patterns predicted by prospect theory. They argue that this may be due to the nature of survey data, in which respondents do not independently assess each individual attribute, but instead consider all attributes as a package. Masiero and Hensher (2010) observe loss aversion behaviour in travel route choices. Additionally, by accommodating non-linearity in attributes, they find diminishing sensitivity behaviour in both the gain and loss domains.

The gain-loss framework introduced by Hess et al. (2008) has also been applied in several environmental studies (Lanz et al., 2009; Glenk, 2011; Ahtiainen et al., 2015; Bartczak et al., 2017), and loss aversion is commonly found for some of the attributes. However, one concern about the design in some of these studies is that the unbalanced range of attribute levels in the gain and loss domains may cause loss aversion manipulation bias. In the experiments of Walasek and Stewart (2015), loss aversion appears to be larger when the range of the monetary good in the gain domain is larger than that in the loss domain. Their explanation is that individuals use a series of ordinal comparisons in memory, which is consistent with sampling theory (Stewart et al., 2006). In decision by sampling, individuals are sensitive to the rank of the amounts in the provided range, rather than the absolute values.

Additionally, although fixed reference points are commonly assumed and presented in the status quo option, Glenk (2011) and Ahtiainen et al. (2015) argue that data unavailability about the current status of the environment and the heterogeneous nature of environmental conditions within the study site suggest that fixed reference points may not be appropriate. Instead, they propose to use individual-specific perceptions about present environmental situation as reference points.

2.2.3 Studies on the effects of social capital on environmental and loss aversion preferences

Another interesting avenue of exploration is the role of social capital in environmental management. Various definitions of social capital have been proposed. Coleman (1990) presents a neutral definition of social capital, namely anything that facilitates individual and social collective actions through networks and norms, etc. Putnam et al. (1993) emphasize the moral side of social capital beyond pure self-interest, and underline the importance of trust and reciprocity in communities for the formation of social capital. Despite little consensus on the concept and measures of social capital (Fukuyama, 2001), one can infer that social capital, which originated from moral obligations, affects individuals' decision to take collective actions across the whole community through different kinds of social networks and interpersonal emotions.

Studies have found evidence that social capital is relevant to environmental and resource management as it affects individual and collective behaviour (Pretty, 2003; Cramb et al., 2005; Liu et al., 2014). In the CVM literature, effects of social capital have been analysed through aspects of social trust, social norms and social networks. Most studies have found that social trust and norms are positively related to WTP for environmental protection (Zhang et al., 2006; Polyzou et al, 2011; Halkos and Jones, 2012; Jones, Malesios, et al., 2009; Jones, Evangelinos, et al. 2012; Jones, Clark, and Malesios, 2015), while the effects of social networks on WTP and other pro-environmental behaviours are inconsistent (Halkos and Jones, 2012; Jones, Clark, and Malesios, 2015). Other social capital factors that may affect WTP include institutional trust (Halkos and Jones, 2012) and reciprocity (Zhang et al., 2006). The effects of social capital have also been confirmed in several DCE studies in forest management and community adaptation for climate change (Smith et al., 2012; Hagedoorn et al., 2019).

Furthermore, social capital indicators (i.e., social trust and norms) are closely related to social distance (Putnam, 2007; Kong, 2011; Gvozdanović, 2012). Individuals who have higher social capital scores may have lower level of social distance and are more tolerant towards other members in society. Various studies have confirmed the roles of trust and social norms in environmental protection and energy conservation (Cvetkovich and Winter, 2003; Nyborg et al., 2006; Cialdini, 2007; Allcott, 2011; Costa and Kahn, 2013). Thus, it is expected that people who are socially closer to others are more likely to consider environmental benefits enjoyed by others, and therefore contribute in environmental management.

Interestingly, social distance is also relevant to loss aversion. Studies have found that loss aversion is lower in decisions made for others than for oneself (Polman, 2012; Mengarelli et al., 2014; Zhang et al., 2017). One of the explanations is that the self-other effect is mediated by emotion.[7] As one's social distance is certainly closer to oneself than others, emotion is more likely to affect oneself than others. Similarly, it is expected that compared with those who are socially distant from others, people who are socially closer in a society may place more emotional attachment to others, and thus more likely

[7] In Neuro-economics, the role of emotion on loss aversion has been confirmed in some studies using functional magnetic resonance imaging method (Tom et al., 2007; Weber et al., 2007; Sokol-Hessner et al., 2009, 2013). This effect is also supported by findings from experimental economics (Campos-Vazquez and Cuilty, 2014). For the effect of self-other preference on loss aversion, as emotional attachment for others is less than emotional attachment to oneself, emphasis on loss in decision making may be less impressive for others than for oneself.

to be affected by loss aversion. Therefore, based on the gain-loss framework, I expect that a positive link between social capital and loss aversion.

2.2.4 Taboo trade-off aversion

In a gain-loss framework, ethical considerations may play an important role when respondents are asked to accept monetary benefits at the expense of environmental degradation. Studies in psychology have shown that respondents may find such actions inappropriate and may be reluctant to exchange public goods for money, as such trade-offs often induce negative emotions, e.g., distress, or even moral outrage (Tetlock et al., 2000; Tetlock, 2003; Hanselmann and Tanner, 2008; Zaal et al., 2014; Daw et al., 2015; Stikvoort et al., 2016). For example, people perceive that there will be hardship in choosing to receive a decreased tax payment at the expense of accepting a scenario where less lives will be saved from a natural hazard. In environmental studies, taboo trade-offs between sacred values (i.e., values that are treated as protected and absolute) and secular values are often seen as problematic and incommensurable. Stikvoort et al. (2016) find that real donation to an environmental protection project is significantly affected by the presence of taboo trade-offs. Zaal et al. (2014) observe significant negative emotions towards trade-offs between life-saving and monetary compensations, yet the effect is significantly reduced when the trade-offs are rhetorically reframed as tragic trade-offs (i.e., monetary compensations are described to be used to support local community).

Chorus et al. (2018) is the first study that incorporates taboo trade-off aversion in DCE. Taboo aversion is accounted for by placing additional penalty on respondents' utility when a policy scenario suggests an increase in traffic injuries/fatalities in exchange for a reduction in tax/traffic time. Different taboo trade-off specifications are examined and the preference of taboo trade-off aversion is supported by significant taboo terms in a generic specification where additional taboo penalty is placed if one or more taboo trade-offs are present in a policy scenario.

2.2.5 Attribute non-attendance

The morally problematic taboo trade-offs may cause respondents to ignore attributes. A typical assumption in DCE is that respondents consider all attributes during the process of decision making. However, an increasing number of environmental studies (Scarpa et al., 2009; Carlsson et al., 2010; Campbell et al., 2011; Alemu et al. 2013; Glenk, Martin-Ortega, et al., 2015; Glenk, Meyerhoff, et al., 2019; Nguyen et al., 2015; Koetse, 2017) and health economics studies (Ryan et al., 2009; Hole, 2011a, 2011b; Hole, Kolstad, and Gyrd-Hansen, 2013; Erdem et al., 2015; Heidenreich et al., 2018) have found that subjects ignore one or more attributes when evaluating choices in DCE. With the exception of instances where attributes are ignored due to truly being considered as unimportant, the use of heuristic strategies to minimize cognitive burden (Carlsson et al., 2010; Hensher et al., 2012) and the perception that the survey design is unrealistic, are common reasons for ANA. Not accounting for ANA in analysis may bias WTP estimates, and it is particularly serious if the cost attribute is ignored. Nevertheless, evidence of cost ANA is not uncommon in the literature, with 90% of the sample in Scarpa et al. (2009), 61% in Campbell et al. (2011)[8] and 85% in Erdem et al. (2015) having been found ignore cost.

To mitigate the influence of ANA, a strand of literature incorporates the information of self-reported ANA in choice modelling (Hensher et al., 2005; Campbell et al., 2008; Carlsson et al., 2010), in which the parameters are set to be zero for the ignored attributes. However, the reliability of the stated ANA has been questioned (Carlsson et al., 2010), and respondents in some cases cannot distinguish between ignoring an attribute completely and simply imposing a low weight on it (Hess et al., 2013). Another strand of literature focuses on inferred ANA, using an equality-constrained latent class (ECLC) model (Scarpa et al., 2009; Campbell et al., 2011, 2012; Glenk, Martin-Ortega, et al., 2015; Erdem et al., 2015).[9] The estimated parameter of an attribute in one class is constrained to zero, with the probability of the class representing the rate of non-attendance, whilst the freely-estimated parameters in other classes reflect the attended preference estimates. WTP estimates are commonly found to be smaller in specifications incorporating ANA than those assuming full attendance. Specifically, Koetse (2017) observed a significant drop in disparity between WTA and WTP after controlling for cost ANA. However, a problem of the ECLC model is that results are likely to be confounded with taste heterogeneity, especially if only one non-zero class is specified (Hensher et al.,, 2012; Campbell et al., 2012, Hess et al., 2013). A more advanced model allows preference heterogeneity to be accounted for within the attended class, which mitigates the problem of confounding (Hess et al., 2013). Additionally, segmenting respondents into more classes may also increase the chance that the probability in the zero-coefficient class is a true reflection of non-attendance (Erdem et al., 2015).

2.3 Study background and experimental design

2.3.1 Study background

The study area of this chapter is Beijing, China, where the Chinese government has been battling against heavy air pollution since 2013, when PM2.5 reached its highest record (Wong, 2013). According to data from the Institute for Health Metrics and Evaluation, there are about 1,600,000

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[8] A significant decrease in the level of cost ANA is found in Campbell et al. (2012) using the same dataset, but with a more flexible model specification in which level-specific ANA is allowed for.

[9] An equivalent modelling technique is the endogenous attribute attendance model (Hole, 2011a, 2011b), in which respondents choose a particular attribute processing strategy in the first stage, and then choose their favoured policy option conditional on the strategy chosen previously. Parameters that need to be estimated in this model are significantly fewer than those in ECLC when non-attendance needs to be estimated for each attribute. This chapter uses the ECLC model, as the only focus here is ANA of the cost attribute.

deaths annually due to air pollution (IHME, 2015). The pollution has triggered both public and official concerns in China, and a number of policies have been implemented in response, for example, using the license plates numbers to restrict car movements in Beijing. However, some measures, which may reduce air pollution at the expense of economic growth and citizens' welfare, are deemed to be too stringent to at least some stakeholders.[10] It thus becomes important for policymakers to decide whether to improve air quality at the expense of economic growth, or to favour economic growth and let air quality deteriorate.

2.3.1.1 Attributes and levels

I selected three attributes, namely health, visibility and cost. These attributes and their levels are based on existing DCE studies on outdoor air pollution (Diener et al., 1997; Jara-Díaz and Vergara, 2006; Yoo et al., 2008; Ghorbani et al., 2011; Tekeşin and Ara, 2014; Rizzi et al., 2014; Tang and Zhang, 2015). Furthermore, I consulted experts to assess the realism and possible correlations among these attributes, and conducted one focus group and 15 interviews to assess validity, relevance and comprehensibility of the survey with Chinese students in the University of Southampton in the UK.

(1) Health

The health outcome is the number of hospital admissions due to air pollution in the study area, which is a common adverse health effect caused by air pollution and ethically less pressing for respondents to consider in choice tasks compared to mortality. The current number of hospital admissions due to air pollution is calculated based on the overall hospital admissions in Beijing in 2017 and studies on the relationship between hospital admissions and air pollution (Xu et al., 2016; Zhang et al., 2015; Tian et al., 2018).

(2) Visibility

Poor visibility related to air pollution is strongly associated with PM2.5 in China. Number of "bad visibility days" per month is used to represent the visibility effects. Following Rizzi et al. (2014), I first calculated the number of months that the monthly PM2.5 values were within the 75-100th percentile of the year in 2017. This number was then divided by 12 (i.e. months in a year) to create a ratio representing a percentage of bad visibility days. The ratio was then multiplied by 30 (i.e. the

[10] These measures include shutting down heavy industry plants and curtailing production using non-clean energy in a short time, especially in the coal and steel industries (Feng, 2018).

number of days in a month) to approximate the current number of “bad visibility days” per month in Beijing.

(3) Cost

The household electricity, gas and central heating bill is chosen as the payment vehicle, where households pay (get compensation) through the increase (decrease) of their bill for local air quality improvement (accepting local air deterioration). Such bill changes are frequently used to support environmental services in China (Sun et al., 2016; Sergi et al., 2019). Furthermore, such a payment vehicle has broad appeal and relevance as almost all citizens in Beijing pay electricity, gas and central heating bills, and the related energy industries are largely responsible for air pollution in the local area. Thus, money raised by the government through imposed energy bill changes can be earmarked for the installation of new technologies in these targeted industries in an effort to improve their environmental performance.

To determine the levels of the cost attribute, I referred the results in a governmental report (World Bank, 2007), where the economic loss due to the effect of air pollution on health is estimated. The national-level estimate was then divided by the population of Beijing in 2017 (National Statistical Bureaus of China, 2017) to calculate the estimated economic loss caused by air pollution per person. Using this estimate as a starting point, the preliminary cost range was generated and then pre-tested in focus groups and personal interviews (see Appendix D.3 for the detailed procedures of questionnaire pre-testing). Initial feedback from the pre-tests suggested that the levels of the cost attribute were too small to be considered in attribute trade-offs. The cost level was then increased and pre-tested repeatedly, until most of the respondents noted that the levels were sufficient to be considered in attribute trade-offs (Kløjgaard et al., 2012).

The final attribute levels are presented in Table 2.1. An example of the choice card that was presented to respondents is given in Figure 2.2. A description on the calculation of the current level of each attribute is listed is Appendix A.1.

Table 2.1 Attributes and levels (Chapter 2)

Attributes	**L-3**	**L-2**	**L-1**	**Current Situation**	**L1** [a]	**L2**	**L3**
Health effect (1000 hospital admissions/year)	150 [c]	145	140	130	120	115	110
Visibility effect (bad visibility days/month)	/	12	10	8	6	4	/
Change in electricity, gas and heating Bill (RMB/month)	500 RMB [b] decrease	300 RMB decrease	100 RMB decrease	No change in bill	100 RMB increase	200 RMB increase	500 RMB increase

Note: (a) L1, L2 and L3 are possible levels for environmental improvements (or bill increase for the cost attribute); L-1, L-2 and L-3 are possible levels for environmental deteriorations (or bill reduction for the cost attribute); Current Situation is the level of attributes under current air pollution implementation. (b) According to China National Bureau of Statistics, the deposable income per capita in 2017 in China is 25,974 RMB (i.e., £2,966, according to the exchange rate on 06/09/2019). (c) The annual average PM2.5 (one of the main pollutants of air pollution) level in Beijing is 58ug/m3 in year 2017, while the PM2.5 requirement for class I air quality is <15ug/m3 and is <35ug/m3 for the class II air quality. Therefore, an assumption of maximum 15% air quality change seems reasonable within the context of this study.

	Policy A	Policy B	Current policies
Health (hospital admissions/year)	**145** thousand per year (**15** thousand **more** or **11%** more) 	**120** thousand per year (**10** thousand less or **7.5%** less) 	**130** thousand per year (no change) 
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)	**4** days of bad visibility per month (**4** days less)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	**100** RMB decrease/month （**1,200** RMB decrease/year） 	**100** RMB increase/month （**1200** RMB increase/year） 	No change in bill

Figure 2.2 An example of choice sets (Chapter 2)

2.3.2 Experimental design and procedures

I constructed a D-efficient fractional-factorial design with two blocks, with each block containing ten choice sets (i.e., choice cards), using the Ngene software version 1.2.0. Each choice set consists of two policy alternatives plus a status-quo option, with the current state of air-pollution and its effects in Beijing as its levels. Choice cards were randomly presented to individuals to minimize order effects. Restrictions on experimental design were imposed to avoid unrealistic combinations in choice sets.[11] [12] Note that in this design, current attributes levels in the status quo option are allowed to enter into the policy alternatives to reflect the possibility that attributes levels in new policies could stay the same as their current levels.

Participants were first presented with a participation and a consent forms. After agreeing to participate, respondents were given an introduction on the issues of air pollution and relevant governmental policies. Next, a warm-up DCE question intended to familiarize respondents with the question format (WHO, 2012), followed by ten DCE scenarios, in which people were asked to choose a preferred option among Policy A, Policy B and Current policies (i.e., the status quo option) (see Figure 2.2). At completion, respondents were asked questions about the experiment itself and a set of socio-demographic questions. Ethical approval for the survey was obtained from the Ethics Board of University of Southampton in the UK (ERGO reference number: 30107 A4).

Data collection was conducted through a reputable Chinese marketing company, which administered the survey through an online platform. Respondents from Beijing were randomly sampled and were provided with a personalized link that led them to their assigned questionnaire. Data quality was controlled by setting a minimum time before respondents were able to skip to "Next Page" to ensure that respondents would spend sufficient time on reading the scenario description. Respondents who successfully finished the questionnaire would obtain eight credit points in the marketing company's system, exchangeable for 8 RMB or other equivalent consumption goods.

2.3.3 Social capital questions

Attitudes towards social trust and social norms are used to measure social capital in this context (see Appendix A.2 for detailed questions presented in the questionnaire). To assess social trust, two general

[11] In an alternative, the bill cannot be decreased (increased) if both health and visibility attributes improved (deteriorated).
[12] Note that in experimental design, health, visibility and the cost attributes are allowed to vary independently. In order to reduce confusion, scientific explanations about the separable health and visibility effects were provided before the DCE. Respondents were told that the deterioration could happen, because given the limited financial resources, the government will have to make a decision as to which air pollution effect (i.e., either health or visibility) to deal with first; less implementation on health or visibility will cause the situation of that effect to be worsened.

questions were used, one selected from the World Value Survey (Inglehart et al., 2014) and the other from the General Social Survey 2016 (Smith et al., 2018). These questions have frequently used to elicit social trust attitudes in large field surveys. Another two context-specific questions were constructed to elicit social trust attitudes based on the context of air quality.

One general social norm question was used to elicit individuals' acceptance of non-compliance behaviour. Additionally, based on Cialdini et al. (1990)'s categorisation of social norms and the wording of social norm questions in other contexts (Thøgersen et al, 2008; le Coent et al, 2018), two context-specific social norm questions were constructed to elicit perceptions about the descriptive norm and injunctive norm.[13] Since the effect of social norms could be mediated by personal norms (Schwartz, 1977; Thøgersen et al, 2006), a personal norm question was also included.

[13] Here, a descriptive norm describes perceptions of what others will do and an injunctive norm describes perceptions of what others think everybody should do (Cialdini et al., 1990).

2.4 Modelling framework

DCE modelling is based on random utility theory as developed in McFadden (1974). It assumes that individuals are rational and make decisions to maximise their utility. The basic utility function can be written as:

$$U_{ni} = v_{ni} + \varepsilon_{ni} = \beta X_{ni} + \varepsilon_{ni} \tag{2.1}$$

where v_{ni} is the value function of alternative *i* chosen by individual *n*, which represents the deterministic part of the utility function. X_{ni} is an attribute vector (including the health, visibility and cost attributes), while ε_{ni} is an error term which is assumed to be independent and identically distributed (IID).

2.4.1 Asymmetric specification: Loss aversion

According to the classic economic theory, individuals have symmetric responses to same-sized improvements and deteriorations in attributes, which implies that the effect of a change in an attribute (either an improvement or a deterioration) can be captured by the same parameter. As such, the value function of a linear symmetric model is:

$$v_{ni} = ASC_{SQ,i} + \beta_H H_{ni} + \beta_V V_{ni} + \beta_C C_{ni} \tag{2.2}$$

Here, $\beta_H, \beta_V, \beta_C$ are parameters associated with the three attributes, namely health (H), visibility (V) and policy cost (C). $ASC_{SQ,i}$ is an alternative specific constant term for the status quo alternative, which captures any unobserved effects of the status quo option relative to the proposed alternatives on utility, in addition to attribute effects.

Next, a linear asymmetric specification is used to reflect the asymmetrical responses in utility between the gain and loss domain. This specification allows researchers to model the effects of an attribute's improvements and deteriorations on utility separately, and it requires two parameters per attribute, one on the gain and the other one on the loss domain. The linear asymmetric value function is specified in Equation 2.3.

$$v_{ni} = ASC_{SQ,i} + \beta_H^{imp} H_{ni}^{imp} + \beta_V^{imp} V_{ni}^{imp} + \beta_C^{inc} C_{ni}^{inc} + \beta_H^{det} H_{ni}^{det} + \beta_V^{det} V_{ni}^{det} + \beta_C^{dec} C_{ni}^{dec} \tag{2.3}$$

where H^{imp}= max(H_{SQ}–H, 0) indicates an improvement in health attribute relative to its reference point (i.e., the current health level), and H^{det} = max($H - H_{SQ}$, 0) indicates a deterioration in health attribute relative to its reference point. The same transformation is applied to the visibility attribute. In a similar fashion, C^{inc} and C^{dec} represent increased and decreased cost, respectively, relative to the current level of bill (i.e., no change in bill).

Hence, the first testable hypothesis is:

Hypothesis 1 (H1): Respondents prefer avoiding losses over acquiring gains in air quality changes

According to prospect theory, the null hypothesis for loss aversion in health attribute is $H1_0$: $|\beta_H^{\text{imp}}| \geq |\beta_H^{\text{det}}|$, and the alternative hypothesis is $H1_1$: $|\beta_H^{\text{imp}}| < |\beta_H^{\text{det}}|$. A rejection of null hypothesis means that loss averse behaviour is detected.

Instead of testing H1 by comparing unconditional means of attributes in a mixed logit model, I examine this hypothesis by comparing individual-specific conditional means inferred from corresponding unconditional estimates (the mixed logit model and the calculation process of obtaining conditional estimates will be introduced in details in Section 2.4.5).[14] Additionally, bounded normal distributions are imposed on the health and visibility random parameters by setting standard deviations equal to their means. Imposing constraints enables one to obtain coefficients with signs that are more behaviourally acceptable (Hensher and Greene, 2003).[15] This is important especially when conditional means are used and linked with individual-specific characteristics in Hypothesis 3 (will be introduced in Section 2.4.3).

2.4.2 Non-linear asymmetric specification: Diminishing sensitivity

I assess the diminishing sensitivity behavioural pattern by investigating the shape of the utility curve in the gain and loss domain. Such tests can be conducted through a non-linear asymmetric value function where additional quadratic terms of the health improvement and deterioration variables are introduced in the specification. [16] The equation is as below:

[14] Note that in this study, H1 can be tested in a traditional way (i.e., by comparing the unconditional means of attributes in the gain and loss domains). As conditional means will be used to test H3, testing H1 using conditional means here is for consistency purpose. The results of H1 testing with unconditional means are reported in footnote 26.
[15] However, reduced number of free parameters imply a poorer model fit. Empirically, it seems that researchers have to balance the strengths and weaknesses of imposing constraints on random parameters.
[16] This chapter did not attempt to test the non-linear visibility effect, and thus this attribute was assumed to be linear in each domain in experimental design. This choice is a compromise between design power and cognitive burden.

$$v_{ni} = ASC_{SQ,i} + \beta_H^{imp} H_{ni}^{imp} + \beta_H^{\text{imp2}} (H_{ni}^{imp})^2 + \beta_H^{det} H_{ni}^{det} + \beta_H^{det2} (H_{ni}^{det})^2 + \beta_V^{imp} V_{ni}^{imp} + \beta_C^{inc} C_{ni}^{inc} + \beta_V^{det} V_{ni}^{det} + \beta_C^{dec} C_{ni}^{dec} \tag{2.4}$$

A complete behavioural pattern of diminishing sensitivity requires the value function of an attribute to be concave in the gain domain and convex in the loss domain, which gives rise to the second testable hypothesis:

Hypothesis 2 (H2): Utility shows diminishing sensitivity to health changes relative to the current health level

The null hypothesis is $H2_0$: $\beta_H^{\text{imp2}} \geq 0$ and $\beta_H^{det2} \leq 0$, while the alternative hypothesis is $H2_1$: $\beta_H^{\text{imp2}} < 0$ and $\beta_H^{det2} > 0$. A rejection of null hypotheses means diminishing sensitivity for the health attribute is detected. To be consistent with the linear asymmetric specification, same constraints are imposed on the linear terms, but no constraint is imposed on the quadratic terms.[17]

2.4.3 The effects of social capital

According to Becker (1974)'s social interaction theory, the utility function for the consumption of an environmental good consists of a private and a public utility. Assuming that the two components are linear and separable, the ratio of the public utility to the private utility measures the weight of an individual's public relative to private utility, and is equal to 1 if utility gain (loss) from the public and private consumption is equal. Heterogeneity can be introduced if the ratio differs for people with high and low social capital. Therefore, for a given environmental good (given a prior assumption that there is no difference in the level of private utility between the high and low social capital groups), if overall utility for the high social capital group is observed to be higher than that for the low social capital group, it implies that the ratio of the public utility to the private utility for the high social capital group is larger than that for the low social capital group.

This expectation leads to the third hypothesis:

Hypothesis 3a (H3a): Individuals with higher social capital values are more sensitive towards environmental change

[17] I do not impose constraint on the quadratic terms, as this specification will not be linked with individual characteristics in further hypothesis testing.

H3a implies that a positive correlation between social capital and air quality improvement is expected. On the other hand, people with higher social capital is expected to experience higher level of disutility when air quality deteriorates. To test Hypothesis 3a, factor analysis is used to construct two social capital indices from two sets of social capital variables, namely social trust and social norms. Each resulting index is subsequently dichotomized at the median, creating two dummy variables of high and low values. To test the relationship between social capital and people's environmental preferences for air quality changes, I regress the conditional means of the health and visibility attributes retrieved from the linear asymmetric specification on the dummy variables of social trust and social norms. Variables representing age, education, income and gender are added to the regression to control for demographic effects.[18] The regressions are as follows:

$$H_n^{imp} = \beta_{sc}^{imp} D_n^{sc} + \zeta Demo_n \quad (2.5)$$

$$H_n^{det} = \beta_{sc}^{det} D_n^{sc} + \zeta Demo_n \quad (2.6)$$

where H_n^{imp} (H_n^{det}) represents the conditional estimate of the health improvement (deterioration) variable for individual n. D_n^{sc} represents the dummy variables for different social capital indicators (i.e., social trust and social norms); it is equal to 1 if individual n belongs to the high social capital group, and equal to 0 if individual n belongs to the low social capital group. $\mathrm{Demo_n}$ is a vector representing the demographic status of individual n. For the health attribute, the null-hypotheses of H3a are $H3a_0$: $\beta_{sc}^{imp} \leq 0$ and $\beta_{sc}^{det} \geq 0$, and the alternative hypotheses are $H3a_1$: $\beta_{sc}^{imp} > 0$ *and* $\beta_{sc}^{det} < 0$. A rejection of the nulls implies that the high social capital group reacts stronger towards environmental changes than the low social capital group. The same tests are applied to the visibility attribute.

Furthermore, under the framework outlined in Section 2.1, people with high social capital are expected to feel less social distance with others in society, and thus are more emotionally attached to others, which results in higher loss aversion compared to those with low social capital values.[19]

Hypothesis 3b (H3b): Individuals with higher social capital values are more loss averse towards environmental change

[18] As supplementary analysis, I also construct a social information index, reflecting the informational effects of social networks based on survey questions asking respondents' knowledge and experience of air pollution. The social networks (information) index is constructed and dummy coded in a similar way as I did for the social trust and norms indices. The results are reported in footnote 30.

[19] In this study, it is assumed that the loss aversion preferences for private goods are the same between the low and the high social capital groups, and are higher than loss aversion preferences for public goods (which is consistent with literature findings). Although these assumptions may not be desirable, I acknowledge that the experimental design does not permit the detection of separate loss aversion preferences for the private and public goods.

In the tests of H3b, individual-specific conditional means are again used to construct individual-specific loss aversion index. The construction of the loss aversion indices are presented in Equation (2.7) and (2.8):

$$LA^{health} = \frac{H^{det}}{H^{imp}} \tag{2.7}$$

$$LA^{visibility} = \frac{V^{det}}{V^{imp}} \tag{2.8}$$

where LA^{health} and $LA^{visibility}$ represent the loss aversion indices of the health and visibility attributes respectively. To test H3b, I regress loss aversion indices on the dummy variables of social trust and social norms, controlling for demographic effects. In terms of the health attribute, the equation is presented as below:

$$LA_i^{health} = \beta^{sc} D_i^{sc} + \zeta Demo_i \tag{2.9}$$

The null-hypotheses of H3b is $H3b_0$: $\beta^{sc} \geq 0$, and the alternative hypothesis is $H3b_1$: $\beta^{sc} < 0$. A rejection of the null suggests that the high social capital group is more averse to health loss than the low social capital group. The same test is applied to the visibility attribute.

Note that in this study, the distribution of the loss aversion indices are examined before testing H3b. Due to the concern that the results are biased by outliers, a k-means algorithm is applied to detect potential outliers. In addition to the test with a full sample, the detected outliers will be excluded and H3b will be retested. The K-means method partitions the data into clusters, in which individuals belong to the cluster with the nearest mean. Individual loss aversion indices of both the health and visibility attributes are classified into *k* clusters, and the selection of the *k* is based on the rule of thumb that optimal *k* is the one when the reduction of the within-cluster error becomes negligible.

2.4.4 Additional analysis: Taboo trade-off aversion and attribute non-attendance

In the DCE framework, taboo trade-off aversion is accounted for by specifying an alternative-specific taboo term in utility function. The term indicates additional distaste respondents experience when the presented policy option contains taboo trade-off(s), after controlling for the attribute effects. In this study, a trade-off is considered to be a taboo, if a policy option suggests that a deterioration in air quality (i.e., either in health or visibility, or both attributes) can be made in exchange for monetary compensation (i.e., bill reduction). To account for taboo aversion preference, this chapter postulates attribute-specific taboo specifications. The value functions of alternative *i* with the attribute-specific taboo accounted for are specified in Equation 2.10 and Equation 2.11:

$$v_i = ASC_{SQ,i} + \beta_H^{imp} H_{ni}^{imp} + \beta_V^{imp} V_{ni}^{imp} + \beta_C^{inc} C_{ni}^{inc} + \beta_H^{det} H_{ni}^{det} + \beta_V^{det} V_{ni}^{det} + \beta_C^{dec} C_{ni}^{dec} + \beta^{taboo} Taboo_{health,i} \quad (2.10)$$

$$v_i = ASC_{SQ,i} + \beta_H^{imp} H_{ni}^{imp} + \beta_V^{imp} V_{ni}^{imp} + \beta_C^{inc} C_{ni}^{inc} + \beta_H^{det} H_{ni}^{det} + \beta_V^{det} V_{ni}^{det} + \beta_C^{dec} C_{ni}^{dec} + \beta^{taboo} Taboo_{visibility,i} \quad (2.11)$$

where in addition to Equation 2.3, a taboo term is specified. $Taboo_{health}$ ($Taboo_{visibility}$) is a dummy variable, taking the value 1 if the taboo penalty is induced by the health (visibility) attribute.

Another intuitive specification (i.e., Equation 2.12) assumes that an alternative will only be penalized if two taboo trade-offs are shown (i.e., the dummy variable will take the value 1 only if the policy option suggests a monetary compensation for both deteriorated health and visibility).

$$v_i = ASC_{SQ,i} + \beta_H^{imp} H_{ni}^{imp} + \beta_V^{imp} V_{ni}^{imp} + \beta_C^{inc} C_{ni}^{inc} + \beta_H^{det} H_{ni}^{det} + \beta_V^{det} V_{ni}^{det} + \beta_C^{dec} C_{ni}^{dec} + \beta^{taboo} Taboo_{both,i} \quad (2.12)$$

For taboo terms that have significant mean parameters, they will be interacted with variables representing individual characteristics in order to offer insights on the heterogenous effects of taboo aversion preference across social groups. Taboo trade-off aversion is estimated using mixed logit models in which taboo parameters are assumed to be random and normally distributed across individuals.

In order to account for ANA, an equality-constrained latent class (ECLC) model is applied (Campbell et al., 2010; Scarpa et al., 2013; Glenk, Martin-Ortega, et al., 2015). The ECLC model is based on the latent class model (described in Section 2.4.5), with the attribute parameters in some classes being restricted to zero to reflect the presence of attribute non-attendance. As this study is only interested in ANA of the cost attribute, a zero-coefficient is imposed on cost attribute in one of the classes, and the cost coefficients in rest of the classes are freely estimated. Health, visibility and the alterative specific constant are assumed to be homogenous across all classes, as proposed in most of the ECLC applications.[20] In addition, this study makes use of an ECLC-MXL model, in which within-class

[20] Different from Glenk, Martin-Ortega, et al. (2015), current levels are allowed to enter into policy alternatives in this study, and thus it is reasonable to assume that the coefficient of ASC is equal across classes. A detailed discussion can be seen in Glenk, Martin-Ortega, et al. (2015).

preference heterogeneity is accounted for, to minimize estimation bias resulting from an inability to distinguish between ANA and low sensitivity to attributes (Hess et al., 2013). Under the ECLC-MXL model, all attribute parameters in attended classes are assumed to be normally distributed within each class.

2.4.5 Econometric models

Following the various specifications of the deterministic component of the utility function, the error term (ε_{ni}) is assumed to be IID and follow the Extreme Value distribution (Type I). Yet, the IID assumption of the error term is often violated in empirical analysis, implying a lack of preference homogeneity across respondents. Unobserved heterogeneity is modelled through a mixed logit (Hensher and Greene, 2003), where attribute parameters are specified as random, with the utility function now becoming:

$$U_{ni} = \beta_n X_{ni} + \varepsilon_{ni} = \alpha X_{ni} + \zeta_n X_{ni} + \varepsilon_{ni} \tag{2.13}$$

The error term ε_{ni} is still assumed to be IID, however, compared with Equation 2.1, $\beta_n X_{ni}$ is now split to two parts, where α captures the mean of individual preference and ζ_n captures the deviation around the mean. The IID assumption is relaxed as the utility are allowed to be correlated across alternatives. The probability function of subject *n* choosing alternative *i* in choice set *t* in a mixed logit model is given by:

$$P_{ni} = \int (\prod_t \frac{\exp(\beta_n X_{nit})}{\sum_{i=1}^{I} \exp(\beta_n X_{nit})} f(\beta) d\beta \tag{2.14}$$

with $f(\beta)$ being the density function of coefficient β.

An increasingly popular way of interpreting random parameters in mixed logit model is analysing the conditional estimates and link them with individual characteristics (Revelt and Train, 2000; Greene, 2002; Hess, 2010). Researchers can obtain individual-level conditional estimates representing the most likely position of each individual on the pre-assumed distribution. The conditional estimates of individual *n* are written as $\widehat{E_n(w)}$ in Equation 2.15,

$$\widehat{E_n(w)} = \frac{\sum_{r=1}^{R} [L(y_n|W_r) w_r]}{\sum_{r=1}^{R} L(y_n|w_r)} \tag{2.15}$$

where w_r represents the independent multi-dimensional draws, and $L(y_n|w_r)$ gives the likelihood of observing the sequence of choices for individual n given w_r. The benefits of using conditional estimates include mitigating the outlier problem and linking the preference estimates directly to individual characteristics (Hess, 2010).

It should be noted that before using conditional estimates, a test needs to be conducted to see whether the variance of conditional means has captured sufficient amount of the total variance of unconditional estimates (Revelt and Train, 2000; Richter and Weeks, 2016). I will conduct this test before testing Hypothesis 3 in the results section.

An alternative model to account for heterogeneous preferences is the latent class model. Compared with mixed logit model, the latent class model classifies individuals into different segments according to their preference, which helps to explain the sources of heterogeneity better (Boxall and Adamowicz, 2002). In traditional latent class model, preferences are assumed to vary across segments, but are homogenous within each segment. The probability function is given by:

$$P_n = \sum_{q=1}^{Q} H_{nq} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_q X_{njt})}{\sum_{j=1}^{J} \exp(\beta_q X_{njt})}\right]^{y_{njt}} \tag{2.16}$$

where H_{nq} is the probability of individual n belonging to class q, typically specified through a multinomial logit:

$$H_{nq} = \frac{\exp(Z_n \Upsilon_q)}{\sum_{q=1}^{Q} \exp(Z_n \Upsilon_q)} \tag{2.17}$$

where Z_n represents individual characteristics and the Q^{th} parameter vector is normalized to zero for identification purpose. Estimation is based on maximum likelihood and the optimal number of latent classes is determined exogenously through the use of some information criteria, i.e. Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Swait, 1994).

2.4.6 The computation of WTP and WTA estimates in the symmetric and asymmetry specifications

In the symmetric model, WTP is equal to WTA, and both are estimated as the ratio of an environmental attribute parameter (e.g. β_e) to the cost coefficient (e.g. β_c):

$$WTP^{symmetric} = WTA^{symmetric} = \beta_e / \beta_c \tag{2.18}$$

In the asymmetric specification, however, WTP is not necessarily equal to WTA and the ratio takes into account the different coefficients estimated for the gain and loss domains. The WTP and WTA values are calculated as below:

$$WTP^{asymmetric} = \beta_e^{imp}/\beta_c^{inc} \tag{2.19}$$

$$WTA^{asymmetric} = \beta_e^{det}/\beta_c^{dec} \tag{2.20}$$

where β_e^{imp} and β_e^{det} are the coefficients for the environmental improvement and deterioration attributes respectively, and β_c^{inc} and β_c^{dec} are the coefficients of the cost attribute in the gain and loss domains.

The mixed logit models are estimated using Stata 15 and the simulation is based on 500 Halton draws. Models that are used to explore cost ANA (i.e., MNL, ECLC and ECLC-MXL models in Table 2.10) are estimated using the Apollo package in R (Hess and Palma, 2019), with random parameters in the ECLC-MXL models following normal distributions based on 500 Halton draws.

2.5 Results

2.5.1 Description

The final survey was completed by 230 respondents.[21] Sample descriptive statistics are given in Table 2.2. Comparing the characteristics of the sample with those of Beijing general population, the sample tends to be more educated and younger. This is potentially due to the fact that this is a web-based experiment where selected respondents need to be able to have online access, and have registered accounts with the marketing company.[22] For those who completed the survey, I exclude responses with no variation in DCE answers from modelling analysis (i.e., people who always chose Policy A or Policy B, and those who chose the status quo option constantly for the belief that citizens do not need to pay for air quality improvement), which accounts for 1.7% (4 subjects) of the whole sample.

[21] The sample size in this thesis is determined by both the rule of thumb and the financial capacity of the author in data collection. First, the initial decision of sample size was made according to the rule of thumb that a sample of over 100 respondents (per treatment) should be sufficient to provide basic preference data (Pearmain et al., de Bekker-Grob et al., 2015). Second, the author maximised the sample size, subject to budget availability. Note that the author has optimised the experimental design in this thesis using a D-efficient method; the sample size needed therefore is much smaller than that in a conventional orthogonal design (Rose and Bliemer, 2013). A Monte Carlo experiment was conducted before data collection and the results showed that the current designs are able to identify the attribute effects in the hypotheses and research questions mentioned in the thesis at a 5% significance level.

[22] I acknowledge that sampling bias may affect the generalisability of the findings to the population level. The sample in this thesis is younger and more educated relative to the general public in the study area, yet education and age have been found to be correlated with individuals' environmental preferences (Birol et al., 2006; Ruto and Garrod, 2009). Thus, estimates of environmental preference (and hence WTP) in this sample are potentially larger than those among the general public in Beijing. The marketing company provided the service of accessing a more representative sample, yet financial constraints prevented the authors from gaining from this possibility.

Table 2.2 Summary statistics of respondent characteristics

Variables	Sample	General population [c]
Age		
18-25 years	4.8%	21%
25-35 years	46.5 %	23%
35-45 years	39.6 %	19%
45-55 years	7.8 %	18%
>55 years	1.3 %	20%
Gender (male %)	48.2 %	51.2%
Highest level of education completed		
High school or lower	0.4 %	67%
Undergraduate	94.4 %	29%
Postgraduate or higher	5.7 %	4%
Annual gross income (RMB)		
80,000 or less	8.3%	
80,000-200,000	66.5%	
200,000-300,000	19.6%	
300,000 or higher	5.7%	
Income (mean) [a]	168,690	113,073
Responsible for bill [b]	92.2%	
Sample size	230	

Note: (a) The mean of income for the sample is represented by weighted sum of means of each income category; (b) Responsible Bill is the Self- reported responsibility for the household bill (Yes/No). (c) Age and education data for the general population are from the 2010 Population Census of China, and gender and income data are from the Beijing Statistical Yearbook 2017.

2.5.2 Hypothesis 1: Loss aversion

The results of the mixed logit model are presented in Table 2.3. In the symmetric model (model 1), random parameters are assumed to follow normal distributions. The results show that all attribute coefficients are significant and of the expected signs.[23] The significant standard deviations suggest significant preference heterogeneity in the sample. The negative and significant coefficient of the alternative specific constant indicates that respondents generally prefer to choose new policies over staying at the current policy. The negative health and visibility coefficients suggest that improved health (i.e., less hospital admissions due to air pollution per year) or improved visibility (less bad

[23] Here and in all following results of hypothesis testing in this thesis where hypotheses are stated as directional, one-sided tests are used to obtain the significance level.

visibility days per month) increases individuals' utility, while the negative cost coefficient indicates that utility decreases when the bill payment increases.

In the asymmetric model (model 2), attributes are separated according to gain and loss relative to the current attribute levels. A bounded normal distribution, where the standard deviations are set to equal to the corresponding means, is applied to random parameters of attributes. All variables are again found to be significant and have the expected sign, with the exception of the cost decrease variable. The cost decrease variable is insignificant with a negative sign. I will return to explore potential reasons for this unexpected result in Section 2.5.5. The positive sign of the health and visibility improvement variables (i.e., H^{imp} and V^{imp}) implies utility gains, while the negative sign of the health and visibility deterioration variables (i.e., H^{det} and V^{det}) implies utility losses. Additionally, the model fit of the constrained model (BIC=4147) decreases compared with the that without coefficient constraints (BIC=4117),[24] which suggests that obtaining coefficients that are more consistent with behavioural expectations has a cost of a worse model fit.

As I mentioned in Section 2.4.1, conditional estimates (instead of unconditional estimates) are used to test Hypothesis 1. Turning to the results of conditional estimates in Table 2.4. By comparing the individual-level conditional estimates between the gain and loss domains, evidence of loss aversion in preference is found for both the health and visibility attributes. The mean of the conditional means of the health deterioration variable (in absolute value) is significantly larger than that of the health improvement variable (p-value<0.01) according to one-sided t-test.[25] In a similar fashion, loss aversion is also found for the visibility attribute (p-value<0.01). These results are consistent with past studies (Lanz et al , 2009; Glenk, 2011; Ahtiainen et al, 2015; Sergi et al., 2019). Figures 2.3 plots the utility curves of the health and visibility attributes. Thus, the results suggest that the null hypothesis of H1 can be rejected for both the health and visibility attributes.[26]

2.5.3 Hypothesis 2: Diminishing sensitivity

Turning to the non-linear asymmetric model (model 3) in Table 2.3. Consistent with Masiero and Hensher (2010), the negatively significant quadratic term in the gain domain and the positively significant quadratic term in the loss domain (one-sided tests; p-values<0.01) imply a concave value function in the gain domain and a convex value function in the loss domain. Thus, the null hypothesis of H2 can be rejected for the health attribute.

[24] I do not provide results of the asymmetric specification without constraints due to limited space. The model fit (measured by BIC value) improves compared with its symmetric counterpart, which is consistent with gain-loss literature.
[25] Throughout the thesis, I report the results of one-sided tests in the main text for hypotheses that are stated as directional.
[26] I also test Hypothesis 1 from the results of unconditional means of mixed logit instead of conditional means, and the results remain qualitatively unchanged.

Table 2.3 Mixed logit model results: Loss aversion and diminishing sensitivity

	Symmetric model (model 1)		**Asymmetric model (model 2)**		**Non-linear asymmetric model (model 3)**	
Variables [a]	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
C	-0.0005***	(0.0002)				
C^{inc}			-0.0017***	(0.0003)	-0.0016***	(0.0003)
C^{dec}			-0.0001	(0.0002)	-0.0002	(0.0003)
Random parameters (mean)						
ASC SQ	-0.748***	(0.144)	-1.296***	(0.169)	-1.295***	(0.184)
H	-0.712***	(0.085)				
V	-0.112***	(0.020)				
H^{imp}			0.797***	(0.090)	0.997***	(0.102)
H^{det}			-1.339***	(0.123)	-1.367***	(0.122)
V^{imp}			0.070*	(0.037)	0.071*	(0.042)
V^{det}			-0.239***	(0.037)	-0.214***	(0.045)
$(H^{imp})^2$					-0.214***	(0.057)
$(H^{det})^2$					0.169***	(0.058)
Standard deviations of the random parameters						
ASC SQ	1.717***	(0.145)	1.321***	(0.156)	1.334***	(0.161)
H	1.051***	(0.083)				
V	0.185***	(0.022)				
H^{imp}			0.797***	(0.090)	0.997***	(0.102)
H^{det}			-1.339***	(0.123)	-1.367***	(0.122)
V^{imp}			0.070*	(0.037)	0.071*	(0.042)
V^{det}			-0.239***	(0.037)	-0.214***	(0.045)
$(H^{imp})^2$					0.037	(0.173)
$(H^{det})^2$					-0.067	(0.236)

Table 2.3 Continued

Model statistics			
AIC	4063	4091	4073
BIC	4111	4147	4155
Log-likelihood	-2025	-2038	-2025
n (respondents)	226	226	226
n (observations) [c]	6,780	6,780	6,780

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; H is the health attribute assuming linear; H^{imp} (H^{det}) is the health attribute in the gain (loss) domain; V is the visibility attribute assuming linear; V^{imp} (V^{det})is the visibility attribute in the gain (loss) domain; C is the cost attribute assuming linear; C^{inc} (C^{dec}) is the cost attribute for bill increase (decrease); $(H^{imp})^2$and $(H^{det})^2$ represents the quadratic terms of the health attribute in the gain (loss) domain respectively. (b) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; (c) Number of observations is calculated according to the total number of choices times the number of alternatives instead of the conventional measure of number of observations, due to the data structure of Stata, and this also affects the AIC/BIC values. Thus, AIC/BIC values are only used for model comparison in this study, and are not suggested to use for cross-comparison with other studies.

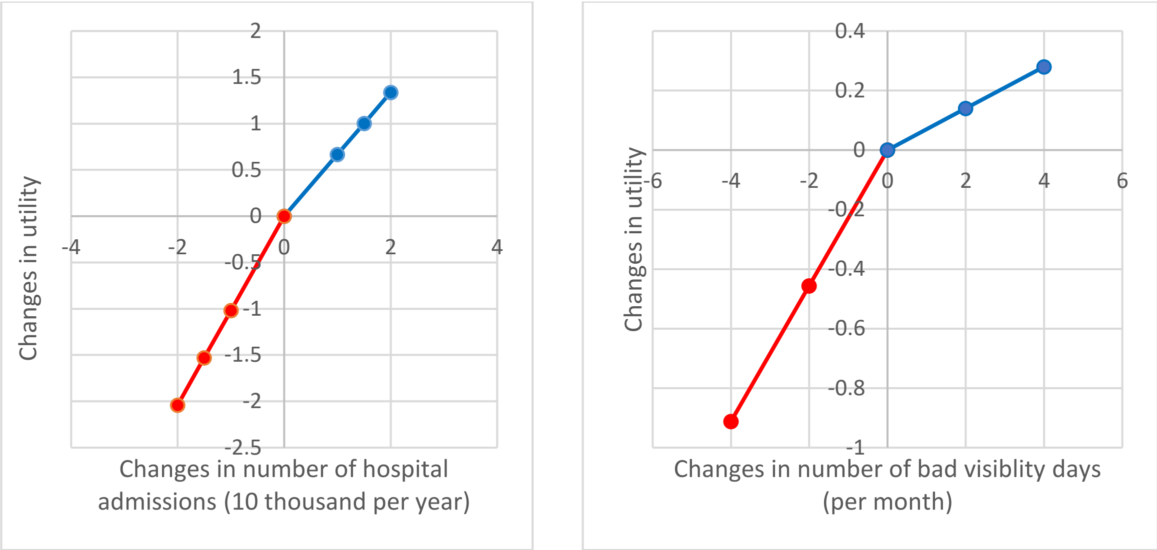

Figure 2.3 Changes in utility as a function of changes in levels of attributes

Table 2.4 Summary statistics of the conditional and unconditional estimates

Variables [a]	Conditional estimates [b]		Unconditional estimates [c]		
	Mean	S.D.	$\hat{u}$	$\hat{\sigma}$	$\frac{S.D.}{\hat{\sigma}}$
H^{imp}	0.669	0.619	0.797	0.797	77.7%
H^{det}	-1.020	1.223	-1.339	1.339	91.3%
V^{imp}	0.070	0.016	0.070	0.070	22.9%
V^{det}	-0.228	0.143	-0.239	0.239	60.0%
ASC SQ	-1.309	0.871	-1.296	1.321	65.9%
n (observations)	226		6,780 [d]		

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; H^{imp} (H^{det}) is the health attribute in the gain (loss) domain; V^{imp} (V^{det}) is the visibility attribute in the gain (loss) domain; (b) Mean refers to the means of the individual-level conditional means across the sample, and S.D. refers to variation in mean estimates. (c) Unconditional estimates are copied from the asymmetric specification in Table 2.3 as comparisons. û is the unconditional mean coefficients and $\hat{\sigma}$ is the unconditional standard deviation coefficients. (d) Number of observations for the unconditional estimates is calculated according to total number of choices times the number of alternatives instead of conventional measure of number of observations due to the data structure used in Stata.

2.5.4 Hypothesis 3: The effects of social capital

First, as mentioned in Section 2.4.5, I investigate whether the variance of conditional means captures sufficient amount of total unconditional variance (Revelt and Train, 2000; Richter and Weeks, 2016). As can be seen in Table 2.4, except for the V^{imp} variable,[27] for every estimated variable, the share of the variance of conditional means on total unconditional variance (i.e., $\frac{S.D.}{\hat{\sigma}}$) is above 60%, which implies that the between-individual variance is sufficient to explain the total variance. Thus, the following hypotheses testing using conditional means are appropriate.

Now turning to the results of Hypothesis 3a. Table 2.5 reports the results of the linear regression of conditional means on social capital indicators (i.e., social norms and social trust), controlling for demographic effects.[28] The coefficients of the social trust and norms dummies are significantly positive (negative) for the health improvement (deterioration) variable (one-sided tests; p-value<0.05 for the social trust coefficient in the health improvement regression and <0.01 for the rest of the coefficients mentioned), suggesting that respondents with high social capital scores assign more utility to health improvements, but experience more disutility from health deterioration than those with low social capital. The social capital coefficients are insignificant for the visibility attribute (one-sided tests; p-values>0.1). Thus, the null hypothesis of H3a can be rejected for the health attribute, but cannot be rejected for the visibility attribute.

Hypothesis 3b intends to test the link between social capital and loss aversion. Before testing H3b, I present the kernel distribution of the constructed loss aversion indices in Figure 2.4a and 2.4b. As can be seen from the figures, the long tails on both sides of the distributions suggest that the results could be biased by outliers. Therefore, a k-means clustering method will be used following the full sample test to detect outliers, and H3b will be tested again in a partial sample where outliers are excluded.

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[27] This implies that for the V^{imp} variable, the variance around the individual means (i.e., within-individual variance) is large. Given that respondents faced finite choice sets in the experiment, in theory the variance around individual means shouldn't be that large. As mentioned by Revelt and Train (2000), model misspecification may cause this issue. However, this is somewhat expected in this study, as constraints are imposed (recall the bounded normal distribution assumption used) when estimating the mixed logit model, and reduced degree of freedom leads to a poorer model fit. However, the aim of imposing constraints is to reduce the proportion of sign violation in attributes. Thus, a trade-off has to be made by researchers. In an additional test that has not been mentioned in this chapter (available upon request), results from a mixed logit model of asymmetric specification without constraints suggest that for this attribute (i.e., V^{imp}), the share of the variance of conditional means on total unconditional variance goes up to 45%. This implies that imposing constraints can partly explain the low share.

[28] Detailed factor analysis results for social capital indicators are provided in Appendix A.3.

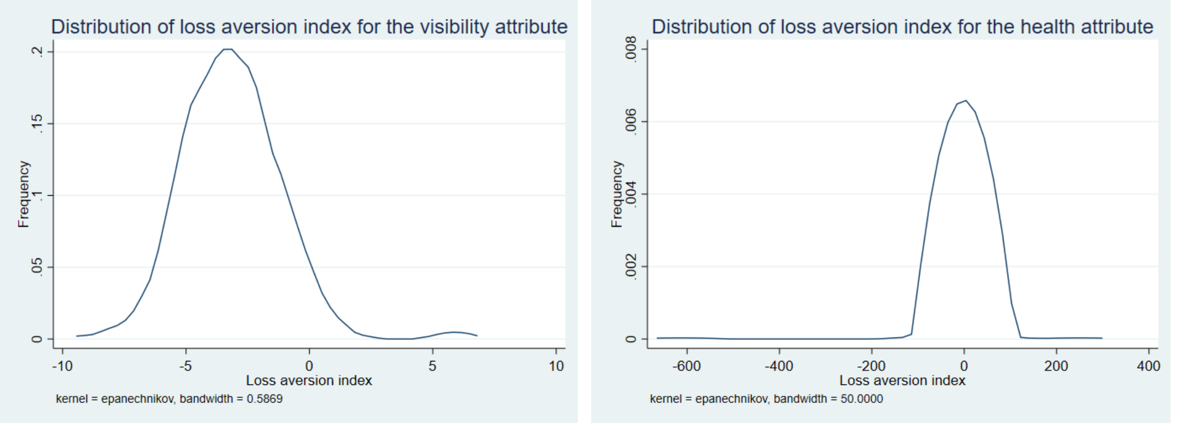

Figure 2.4a & 2.4b The distributions of the constructed loss aversion indices for the visibility and health attributes

The left panel of Table 2.6 shows the full sample results of the linear regression of loss aversion indices on the dummy variables of social capital indicators, controlling for demographic variables. For the health attribute, coefficients of social trust and norms are negative, suggesting that people with high social trust and norms scores are more loss averse (represented by a more negative loss aversion index) than those who have low social trust and social norms values. However, the insignificant coefficients show that in general, the correlation between social capital and loss aversion is not detected for the full sample.

For further investigation, a k-means clustering method is applied to divide the sample into different clusters and detect potential outliers. Table 2.7 presents the mean values of loss aversion indices in each cluster. The loss aversion indices of health and visibility have been classified into five clusters according to the selection rule mentioned in Section 2.4.3. From a first look at the results, it can be seen that 97% of respondents fall into Cluster 1 and only seven respondents with extreme loss aversion indices (compared with those in Cluster 1) belong to other clusters, which implies that there may be some outliers in the sample who have completely different attitudes towards air quality changes. The indices in Cluster 4 and Cluster 5 are even positive, which is counter-intuitive according to the definition of loss aversion. Thus, respondents in Cluster 2 to Cluster 5 are seen as outliers and H3b is examined again only with respondents that belong to Cluster 1. The partial sample results are shown in the right panel of Table 2.6. For the health attribute, the relationship between the social capital indicators and the loss aversion index becomes significant and negative (one-sided tests; p-values<0.05), while it is still insignificant for visibility. Thus, the null hypothesis of H3b for the health attribute can be rejected for the partial sample, but cannot be rejected for the full sample, and the null hypothesis of H3b cannot be rejected for the visibility attribute.[29][30][31]

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[29] As a robustness check, the sample is also partitioned according to other methods that are frequently used to detect outliers. They are the Mahalanobis distance method and Boxplot method. Outliers are defined as those located at the 2.5% head and tail of the distribution of Mahalanobis distance scores. For the Boxplot method, outliers are those whose magnitude of loss aversion indices are out of the range [Q1-1.5IQR, Q3+1.5IQR], with Q1 and Q3 being the first and the third quantile of the sample, and IQR equalling to Q3-Q1. Results suggest that H3b are qualitatively unchanged using the Boxplot method, but only the social trust variable is significant using the Mahalanobis distance method.

[30] As mentioned before, social network is also an important indicator of social capital in the literature, and two questions are used to elicit the informational aspect of social network in this survey. Therefore, H3 is also tested with regard to social networks (information). The results in Table A.3, Appendix A.4 show that for H3a, significant differences in conditional means between the high and low social network groups are observed only for the deterioration scenarios (i.e., health and visibility deterioration). For H3b, significant loss aversion differences between the two groups are only found for the visibility attribute in the partial sample. As it is not clear why social network does not have effects under improvement scenarios in H3a, and why significant effect is observed only for visibility in H3b. The null hypotheses of H3 cannot be rejected for social network (information) in general.

[31] As robustness checks for H3, instead of splitting social capital indicators into two groups, I also divide them into three groups (i.e., a low, a medium and a high group), and include only the lowest and highest group in the regression to provide an enhanced contrast. As shown in Table A.4a and Table A.4b in Appendix A.5, all results remain qualitatively unchanged, except that the null of H3b cannot be rejected for the health attribute in the partial sample. In a further analysis that is not shown in this chapter (available upon request), results from a quantile regression suggest that the relationship between social capital and loss aversion is mostly significant for respondents with medium loss aversion values (e.g., from the 40th to the 75th percentile), and insignificant for those at the lower and higher end of the distribution, implying that the results are sensitive to extreme values.

Table 2.5 OLS regressions of conditional estimates on different social capital indicators

	H^{imp} [a]		H^{det}		V^{imp}		V^{det}	
Variables [b]	**Social trust**	**Social norms**	**Social trust**	**Social norms**	**Social trust**	**Social norms**	**Social trust**	**Social norms**
Social trust	0.160*		-0.543***		0.002		-0.013	
	(0.086)		(0.163)		(0.002)		(0.020)	
Social norms		0.359***		-0.590***	-0.000	0.002		-0.004
		(0.083)		(0.167)	(0.001)	(0.002)		(0.020)
Age	-0.045	-0.061	-0.073	-0.029	0.000	-0.001	0.007	0.008
	(0.052)	(0.050)	(0.110)	(0.109)	(0.001)	(0.001)	(0.012)	(0.012)
Income	0.063**	0.040	-0.087	-0.067	0.003	0.000	0.001	0.001
	(0.027)	(0.026)	(0.057)	(0.058)	(0.002)	(0.001)	(0.007)	(0.007)
Gender	-0.094	-0.142*	0.019	0.110	-0.001	0.002	-0.016	-0.015
	(0.075)	(0.072)	(0.147)	(0.147)	(0.003)	(0.002)	(0.017)	(0.018)
Education	-0.105	-0.089	0.219	0.219	0.069***	-0.001	0.020	0.021
	(0.108)	(0.101)	(0.216)	(0.216)	(0.010)	(0.003)	(0.029)	(0.029)
Constant	0.850**	0.958**	-0.679	-1.057	-0.000	0.070***	-0.333***	-0.342***
	(0.412)	(0.390)	(0.847)	(0.825)	(0.001)	(0.010)	(0.097)	(0.095)
Model statistics								
n(observation)	226	226	226	226	226	226	226	226
R-squared	0.057	0.118	0.075	0.080	0.015	0.015	0.025	0.023

Note: (a) H^{imp}, H^{det}, V^{imp} and V^{det} represent individual-level conditional means; H^{imp} (H^{det}) represents the health attribute in the gain (loss) domain, and V^{imp} (V^{det}) represents the visibility attribute in the gain (loss) domain. (b) Social trust (Social norms) is a dummy variable, equalling to 1 for the high social trust (social norms) group and equalling to 0 for the low social trust (social norms) group; Age is the midpoints of ranges of respondents' age (in year); Income is a categorical variable that represents the midpoints of ranges of respondents' annual incomes (in RMB); Gender is a dummy variable taking the value 1 for male and 0 for female; Education is respondents' highest education level; (c) Standard errors of the means in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6 OLS regressions of loss aversion indices on different social capital indicators

	Full sample				**Partial sample**			
	LA^{health} [a]		$LA^{visibility}$		LA^{health}		$LA^{visibility}$	
Variables [b]	**Social trust**	**Social norms**	**Social trust**	**Social norms**	**Social trust**	**Social norms**	**Social trust**	**Social norms**
Social trust	-3.102		-0.157		-0.895*		-0.117	
	(5.601)		(0.276)		(0.500)		(0.280)	
Social norms		-5.456		0.155		-1.001*		0.112
		(5.199)		(0.270)		(0.526)		(0.273)
Age	2.229	2.518	0.126	0.133	0.189	0.270	0.144	0.149
	(2.646)	(3.009)	(0.162)	(0.159)	(0.317)	(0.332)	(0.165)	(0.161)
Income	0.860	1.171	0.191**	0.166*	-0.123	-0.085	0.205**	0.188**
	(1.251)	(1.243)	(0.095)	(0.094)	(0.182)	(0.180)	(0.097)	(0.096)
Gender	-1.397	-0.639	-0.098	-0.109	0.142	0.307	-0.080	-0.090
	(5.566)	(4.822)	(0.234)	(0.236)	(0.493)	(0.498)	(0.264)	(0.267)
Education	2.565	2.379	0.202	0.231	-0.203	-0.179	0.266	0.288
	(2.903)	(2.765)	(0.357)	(0.353)	(0.614)	(0.583)	(0.356)	(0.352)
Constant	-19.34	-21.45*	-5.013***	-5.129***	-0.279	-1.040	-5.396***	-5.491***
	(12.25)	(11.13)	(1.210)	(1.161)	(2.284)	(2.240)	(1.213)	(1.162)
Model statistics								
Observations	226	226	226	226	219	219	219	219
R-squared	0.005	0.007	0.034	0.034	0.022	0.025	0.039	0.039

Note: (a) LA^{health} is the loss aversion index of the health attribute; $LA^{visibility}$ is the loss aversion index of the visibility attribute; (b) Social trust (Social norms) is a dummy variable, equalling to 1 for the high social trust (social norms) group and equalling to 0 for the low social trust (social norms) group; Age is the midpoints of ranges of respondents' age (in year); Income is a categorical variable that represents the midpoints of ranges of respondents' annual incomes (in RMB); Gender is a dummy variable taking the value 1 for male and 0 for female; Education is respondents' highest education level; (c) Standard errors of the means in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 2.7 Individual-level loss aversion indices by clusters

Clusters	**n(observations)**	**Mean** [a]	
		$\mathrm{LA}^{\mathrm{health}}$	$\mathrm{LA}^{\mathrm{visibility}}$
1	219	-1.139 [b]	-3.139
2	1	-615.751	-3.091
3	2	-74.893	-2.500
4	1	249.576 (+)	-4.950
5	3	42.822 (+)	-3.190

Note: (a) LA_s^{health} is the loss aversion index of the health attribute; $\mathrm{LA}_s^{visibility}$ is the loss aversion index of the visibility attribute; (b) All the signs of loss aversion indices should be negative by its definition, except those with the symbol (+), indicating positive loss aversion indices.

2.5.5 Additional analysis: Taboo trade-off aversion and cost attribute non-attendance

An insignificant cost attribute is observed when cost is described as monetary compensation (i.e., bill reduction) as a result of air quality deterioration (as shown in Table 2.3), which leads to an inability to calculate WTA in Section 2.5.6.[32] The insignificant cost attribute generally means that respondents are insensitive to the variation in policy cost. This is also found in Lanz et al. (2009) where attribute gains and losses are separately presented in utility function. This section investigates whether taboo trade-off aversion and ANA to the cost attribute can provide any explanations for the counter-intuitive results of the cost decrease variable.

2.5.5.1 Taboo trade-off aversion

Results from the mixed logit models with additional taboo terms are shown in Table 2.8. Model fit improvement (measured by BIC) is observed only in the specification accounting for the health taboo term (model 3), compared with the MXL model without additional taboo terms (model 1). Similarly, among all taboo aversion specifications, only the taboo term in model 3 (attribute-specific taboo: health) is significant at 10% and of expected sign (i.e., negative). The results from model 3 imply that presenting taboo trade-off to respondents leads to a non-trivial disutility, in addition to the attribute effects. Given that in this experiment, there is at least one taboo trade-off when a policy scenario contains a bill decrease, taboo trade-off aversion may lead a large number of respondents ignore the scenarios of bill reduction in their decision-making, which could be an explanation of the insignificant

[32] Different specifications (i.e., different distributional assumptions, such as normal and lognormal distributions, and higher number of draws) were applied on the cost decrease variable. Results suggest that the cost decrease variable is still insignificant.

cost decrease variable. Additionally, given the large standard deviation of the taboo term relative to its mean, it is necessary to explore the heterogeneity effects of taboo aversion preference on different social groups using model 3. Results from Table A.6 in Appendix A.7 suggest that respondents with higher social norms and those who stated that air quality deterioration is unacceptable, obtain significantly larger disutility when taboo trade-offs present.

Table 2.8 Results of mixed logit model with taboo trade-off aversion incorporated

	MXL without taboo (Model 1)		**Both taboos (Model 2)**		**Attribute-specific taboo: health (Model 3)**		**Attribute-specific taboo: visibility (Model 4)**	
Variables [a]	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
ASC SQ	-1.315***	1.259***	-1.319***	1.275***	-1.371***	1.447***	-1.302***	1.361***
	(0.187)	(0.177)	(0.189)	(0.178)	(0.197)	(0.169)	(0.191)	(0.171)
H^{imp}	0.586***	1.120***	0.615***	1.135***	0.584***	1.101***	0.606***	1.136***
	(0.113)	(0.120)	(0.118)	(0.122)	(0.113)	(0.121)	(0.116)	(0.120)
H^{det}	-0.951***	1.648***	-0.955***	1.669***	-0.909***	1.562***	-0.975***	1.722***
	(0.151)	(0.154)	(0.153)	(0.158)	(0.161)	(0.159)	(0.153)	(0.163)
V^{imp}	0.064*	0.185***	0.067*	0.200***	0.0570	-0.157***	0.071*	-0.182***
	(0.038)	(0.050)	(0.038)	(0.050)	(0.038)	(0.052)	(0.038)	(0.048)
V^{det}	-0.169***	0.298***	-0.182***	0.305***	-0.190***	0.323***	-0.186***	0.288***
	(0.042)	(0.046)	(0.046)	(0.048)	(0.043)	(0.050)	(0.047)	(0.049)
C^{inc}	-0.0016***		-0.0017***		-0.0016***		-0.0017***	
	(0.0003)		(0.0003)		(0.0003)		(0.0003)	
C^{dec}	-0.0004		-0.0004		-0.0003		-0.0005	
	(0.0003)		(0.0003)		(0.0004)		(0.0003)	
Taboo Penalty			0.055 (0.206)	0.725 (0.496)	-0.438* (0.246)	-1.719*** (0.240)	0.041 (0.159)	0.772*** (0.225)
Model statistics								
Log-likelihood	-2007		-2006		-1988		-2004	
BIC	4119		4135		4099		4130	

Note: (a) $ASC\ SQ$ is the alternative specific constant for the "current policies" option; H^{imp} (H^{det}) is the health attribute in the gain (loss) domain; V^{imp} (V^{det}) is the visibility attribute in the gain (loss) domain; C^{inc} (C^{dec}) is the cost attribute when the bill is specified as increase (decrease*);* Taboo Penalty is the taboo term capturing preference of taboo trade-off aversion, the definition of which varies in different taboo specifications. (b) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

2.5.5.2 Cost attribute non-attendance

Table 2.9 presents the results of a simple MNL model (model 1), followed by results from two ECLC models (model 2 and model 3) that account for ANA to cost increase and decrease, respectively. Cost is segmented into three classes with Class 1 being the non-attendance class, and the rest of the classes being the attended classes.[33] Other attributes are assumed to be homogenous across classes. More flexible ECLC-MXL models (model 4 and model 5) allow for preference heterogeneity within each class.

The results show that the model fit of all ECLC models shows improvement compared with the basic MNL model (measured by the smaller BIC values), which is a consequence of permitting more segmentations in the cost attribute. The probabilities of respondents being allocated to the non-attendance classes in the ECLC Cost Increase (model 2) and ECLC Cost Decrease (model 3) models are 76% and 50%, respectively, implying a large proportion of ANA to cost during decision making. After preferences are allowed to be heterogeneous within each class in model 4, a further decrease in probability (down to 39%) of ANA to the cost increase variable is observed, indicating a mitigation of the confounding issue between preference heterogeneity and ANA, mentioned by Hess et al. (2013). Yet, a similar effect is not found for the ECLC-MXL Cost Decrease model (model 5).

The cost increase variables are significant and negative in both attended classes (i.e., Class 2 and Class 3) in the ECLC Cost Increase model (model 2). In Class 3, respondents are more averse to bill increase than those in Class 2. The preference for bill decrease is more polarised. As can be seen from the results of the ECLC Cost Decrease model (model 3), 37% of respondents have a negative sign in Class 2, whilst 12% of respondents have a positive sign in Class 3. These results suggest that for those who do not ignore the cost attribute, respondents tend to dislike bill increases to different extents. Importantly, for the bill decrease, while some of them prefer to accept bill reduction, a considerable number of respondents obtain disutility when the scenario of bill reduction is presented.

In summary, the large proportion of respondents' non-attendance to bill reduction, together with a group of respondents who dislike bill reduction, seem to explain the result of insignificant and negative cost decrease variable in the asymmetric specification in Table 2.3.

[33] The model fit (measured by BIC values) is optimal at three classes for both the ECLC Cost Increase and ECLC Cost Decrease models. Another reason to use a 3-class instead of 2-class specification is that previous literature state that allowing more classes in ECLC model can, to some extent, disentangle between weak preferences and ANA, and thus increase the chance that the probability in the zero-coefficient class is the true reflection of non-attendance (Erdem et al., 2015; Koetse, 2017). Results based on a 2-class and a 4-class specifications are presented in Table A.5 in Appendix A.6. Consistent with the literature (Campbell et al., 2012; Koetse, 2017), I observe the trend that the non-attendance probabilities are decreasing when more classes are allowed.

Table 2.9 Main estimation results of cost attribute non-attendance

	MNL (model 1)	**ECLC Cost Increase (model 2)**	**ECLC Cost Decrease (model 3)**	**ECLC-MXL Cost Increase (model 4)**		**ECLC-MXL Cost Decrease (model 5)**	
Variables [a]				Mean	S.D.	Mean	S.D.
ASC SQ	-0.432***	-0.601***	-0.488***	-1.510***	1.143***	-1.429***	1.391***
	(0.123)	(0.126)	(0.126)	(0.199)	(0.228)	(0.203)	(0.198)
H^{imp}	0.416***	0.470***	0.423***	0.685***	1.209***	0.678***	1.267***
	(0.060)	(0.062)	(0.062)	(0.126)	(0.134)	(0.125)	(0.131)
H^{det}	-0.334***	-0.372***	-0.335***	-1.001***	1.869***	-0.943***	1.795***
	(0.063)	(0.064)	(0.065)	(0.164)	(0.172)	(0.164)	(0.193)
V^{imp}	0.095***	0.100***	0.091***	0.069*	0.050	0.065	0.058
	(0.029)	(0.029)	(0.029)	(0.041)	(0.142)	(0.041)	(0.096)
V^{det}	-0.057**	-0.072**	-0.059***	-0.199***	0.367***	-0.202***	0.347***
	(0.028)	(0.030)	(0.029)	(0.050)	(0.049)	(0.050)	(0.050)
C^{inc}	-0.001***		-0.001***			-0.002***	0.005***
	(0.000)		(0.000)			(0.000)	(0.001)
C^{dec}	-0.001***	-0.001***		-0.001***	0.004***		
	(0.000)	(0.000)		(0.000)	(0.001)		
Classes and probabilities [b]							
Class 1 (Cost ANA)		0	0	0		0	
Class 2		-0.007***	-0.005***	-0.003*	0.003**	-0.003*	0.008***
		(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Class 3		-0.036**	0.005***	-0.011**	0.020***	0.025	0.001
		(0.014)	(0.001)	(0.005)	(0.007)	(0.022)	(0.030)
π^1		0.76*** [c]	0.50***	0.39***		0.57***	
		(0.04)	(0.11)	(0.13)		(0.21)	
π^2		0.18***	0.37***	0.42***		0.43**	
		(0.04)	(0.10)	(0.16)		(0.21)	
π^3		0.06***	0.12*	0.19*		0.01	
		(0.02)	(0.07)	(0.11)		(0.00)	

Table 2.9 Continued

Model statistics					
Log-likelihood	-2331	-2266	-2285	-1941	-1945
BIC	4716	4609	4649	4021	4029

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; H^{imp} (H^{det}) is the health attribute in the gain (loss) domain; V^{imp} (V^{det}) is the visibility attribute in the gain (loss) domain; C^{inc} (C^{dec}) is the cost attribute when the bill is specified as increase (decrease); (b) Respondents are segmented to 3 classes under the ECLC and ECLC-MXL models. Class 1 (Cost ANA) is the coefficient for the cost ANA class, with its corresponding class probability being π^1; Class 2 and 3 are the coefficients for the attended cost classes, and the probability of the class attendance are $\pi^2$and π^3, respectively. (c) The standard errors of the class probabilities are calculated using the Delta method. (d) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

2.5.6 WTP and WTA estimates

Table 2.10 presents the means of marginal household WTP and WTA estimates (per month) in Beijing for air quality changes. In the symmetric model, the mean of the marginal WTP for health (for every 10,000 fewer hospital admissions) is 1507 RMB (≈£168.77) per month, which is higher than some studies in other countries using similar attributes (Yoo et al, 2008; Ghorbani et al, 2011).[34] The mean marginal WTP for visibility (for a one-day reduction in bad visibility days) is 237 RMB (≈£26.54) per month. In the asymmetric model, when the health and visibility attributes are specified as separate parameters, marginal WTPs for the health and visibility attributes are reduced compared to those in the symmetric model, which is consistent with Hess et al. (2008) and Masiero and Hensher (2010). The mean marginal WTP for health and visibility under the asymmetric model is 463 RMB (≈51.85) and 41 RMB (≈£4.59), respectively. Furthermore, it is also observed that WTPs for health for respondents with high social capital scores are significantly higher than those with low scores, which reinforces the argument in Hypothesis 3a.[35] However, WTA values cannot be calculated due the insignificant cost decrease variable, which implies that respondents are not sensitive towards the variation of monetary compensation when air quality is described as deterioration.

[34] Carson and Czajkowski (2019) mentioned that the moments of WTP would be undefined under the traditional method of WTP calculation, where the mean WTP is given by the ratio of an environmental parameter to a non-random monetary parameter. Following their suggestions, I impose a (negative) log-normal distribution on the cost increase parameter and constrain its standard deviation to be zero. The WTP of the health (visibility) attribute is then given by the health (visibility) parameter divide by the exponential of the estimated monetary parameter. This process is mathematically equivalent to the calculation method I have used in the main text, whilst the mean WTP should be well-defined. Results in this study show that there is no difference between these two methods.

[35] In WTP comparisons, the method of Krinsky and Robb (1986) is first used to obtain an empirical WTP distribution for each group, in which process the standard deviation obtained from the mixed logit model is used in simulation. The WTP distributions are then compared using the Poe et al. (2005) test to obtain the statistical significance of the WTP differences between the high and low social capital groups.

Table 2.10 The means of the WTP and WTA estimates for the full sample and for different social capital groups

	Variables [a]	Symmetric Full sample	Linear asymmetric (constrained) Full sample	Partial sample (social trust) High [c]	Low [c]	Diff	Partial sample (social norms) High	Low	Diff
		WTP [b]	**WTP**						
Gain	Health	1507 [982, 4110]	463 [332, 668]	817 [458, 2224]	296 [192, 445]	Yes [d]	1032 [565, 3203]	128 [32, 241]	Yes
	Visibility	237 [136, 640]	41 [0, 90]	84 [-11, 236]	25 [-15, 63]	No [d]	18 [-125, 153]	41 [9, 75]	No
		WTA [b]	**WTA**						
Loss	Health	1507 [982, 4110]	/	/	/		/	/	
	Visibility	237 [136, 640]	/	/	/		/	/	

Note: (a) Health represents the health attribute; Visibility represents the visibility attribute. (b) The 95% confidence interval is calculated using the Krinsky and Robb (1986) approach with 2000 draws. (c) High represents individuals in the high social capital group, and Low represents those in the low social capital group. (d) Yes means the WTP difference is significant (i.e., p-value<0.05), whilst No means the WTP difference is not significant (i.e., p-value>0.1).

2.6 Discussion

This study explores the role of social capital in individuals' environmental preferences. It confirms the findings of a positive correlation between social capital and preferences for environmental improvement from previous CVM and DCE studies (Polyzou, et al., 2011; Halkos and Jones, 2012; Smith et al. (2012); Jones, Clark, and Malesios, 2015; Hagedoorn et al., 2019). Under the unique gain-loss framework of this study, social capital is also found to be positively related to respondents' disutility for air quality deterioration. Therefore, this study provides a whole picture of the role of social capital in environmental management. The results imply that in a civilized society where the stock of social capital is high, policies aimed at environmental improvement would easily gain support from the public, and that non-monetary based implementations, such as pro-environmental nudging, could be effective. On the other hand, if the policy goal is to maintain economic growth at the expense of air quality, opposition from citizens with high social capital stock may backfire on policy-makers.

An increasing number of studies have focused on the role of social capital in environmental protection in China (Zhang et al., 2006; Chen, Wang, et al., 2014; Hao et al., 2019; Zhou et al., 2020), and the results are generally consistent with the findings in other countries (i.e., positive correlation between social capital and environmental awareness). Given that various environmental problems have occurred in China in recent years, information sharing within the realm of trusted social connections is important for awareness and collective actions in environmental protection. This is especially true in societies where information about environmental risks is absent or incomplete, due to political censorship (Hao et al., 2019).

This study also contributes to the wider literature on how individual and social characteristics affect people's environmental awareness. Except for demographic influences which are relatively well-documented, stated preference studies also substantiate the effects of environmental attitudes (Luzar and Cosse, 1998; Spash, 2006; Hoyos et al. 2013; Li and Hu, 2018) and psychological factors (Smith et al., 2012; Czajkowski et al., 2017; Boyce et al., 2019) on environmental concerns and pro-environmental behaviour. These studies underline the presence of preference heterogeneity in environmental management across social groups and place an emphasis on the distribution, rather than the mean, of the welfare estimates. From a policy perspective, the non-homogenous nature of the environmental preferences in the society indicates that uniform policy enforcement in environmental management, such as a tax increase for all individuals, may not be widely accepted. This is especially true in a society where a few people get most of the benefits from environmental improvement, while the majority gets little benefit.

This study makes another contribution to the literature on the investigation of the presence of loss aversion in environmental decision making, using a DCE where environmental gains and losses are simultaneously presented in choice scenarios. Results suggest that loss aversion is detected for both environmental attributes, which is consistent with other environmental studies (Glenk, 2011; Ahtiainen et al., 2015). Consistent with most of the studies in gain-loss asymmetry, decreases in WTP estimates are found when loss aversion preference between the gain and the loss is accounted for (Hess, 2008; Masiero and Hensher, 2010; Glenk, 2011; Ahtiainen et al., 2015). The finding suggests that if researchers are interested in measuring both welfare gains and losses from a reference point, an asymmetric model that accounts for non-linear preference between the two domains (instead of an averaged linear effect) is recommended. Except for loss aversion preference, other reasons for this WTP decrease (i.e., disparity between WTP and WTA) have also been mentioned in the literature, including the availability of close substitutes (Hanemann, 1991), experience in trading (Kahneman et al., 1990), features of experimental design (Plott and Zeiler, 2005) and moral character (Biel et al., 2011). These findings imply the bounded rationality of individuals and suggest that more research is needed to understand the WTP-WTA disparities in different situations.

This study did not find evidence of the effects of social capital on individual environmental preferences or on loss aversion for the visibility attribute. One reason could be that respondents see the health effects of air pollution as more important than the visibility effects, and thus pay more attention to health (Diener, 1997), making the health effects more likely to reflect their true preference for air quality.

Consistent with the past studies (Scarpa et al., 2009; Campbell et al., 2011; Erdem et al., 2015), a large percentage of cost ANA is observed. More interestingly, results indicate that a group of respondents even obtain disutility from monetary compensations (i.e., bill decrease) when the policy suggests an environmental deterioration. This study also finds that some respondents obtain disutility when they face attribute trade-offs that are commonly considered as taboo. Although morally-induced non-compensatory behaviour has been studied before (Stevens et al., 1991; Araña and León, 2009), few study has attempted to link taboo trade-off aversion with ANA in SP studies. In this study, moral concern about the tradability between money and the environment seems to be a reasonable behavioural explanation for ignoring and disliking bill reduction scenarios, yet it cannot be formally tested under the current design of this study. An interesting avenue for future research is to formally link taboo trade-off aversion with cost ANA. In addition, it could also be that respondents doubt the realism of the payment vehicle and protest by ignoring the cost attribute (Alemu et al., 2013), yet it was found that most participants in the questionnaire pre-tests believed in the effectiveness of the payment vehicle.

Some limitations are acknowledged in this study. First, the range of levels of the health attribute is potentially limited. In fact, the largest implied health change is 15%, which is relatively low compared to other DCE studies. While the choice of attribute levels in this study was driven by realism in the described scenarios, it is possible that the small magnitude in the health changes may have failed to create salient trade-offs in the choice scenarios. Second, in testing the relationship between social capital and loss aversion, an underlying assumption is that loss aversion preference for the private benefits of clean air of the high social capital group is equal to that of the low social capital group. Albeit reasonable, such an assumption cannot be tested in the current experimental design. Future work could employ designs in which private and public preferences for an environmental good are separately identified in different attributes under the gain-loss framework. Third, although evidence of taboo trade-off aversion is found, the results are not significant in every specification, suggesting that there might be an identification issue. This seems to be not too surprising, as even with a full factorial design, Chorus et al. (2018) reported an inability to estimate an elaborate taboo trade-off specification that evaluates all attribute-specific taboo effects separately. Future work could focus on an optimal experimental design which allows a more identifiable taboo effect. Alternatively, a future study could use attitudinal questions to elicit taboo aversion preferences in order to complement findings from the inferred taboo aversion models.

This study reiterates the importance of incorporating asymmetric environmental preference when both gains and losses are possible in future policy options. This is especially policy-relevant in developing countries where the importance of economic development could surpass the progress in environmental management. As stringent policies in the long-run will harm economic growth, environmental degradation from the current level may be imminent.

2.7 Conclusion

In this chapter, I find the existence of loss aversion for air quality attributes, diminishing sensitivity in both the gain and loss domains for the health attribute. These results confirm the findings stated in prospect theory. This is the first study that investigates the effects of social capital on individual preferences for both environmental improvement and deterioration and on loss aversion using a DCE. Social capital may affect utility through awareness of collective actions and environmental concerns, and understanding preferences heterogeneity by social capital levels is of importance for the acceptability of public policy. The study finds that people with high social trust and social norms scores are more sensitive to the changes of the health effects due to air pollution, than those with low social trust and social norms scores. Furthermore, this study also detects taboo trade-off aversion preference and a large proportion of attribute non-attendance to cost, and this could at least partly explain respondents' insensitivity to bill reduction. It is suggested that future work could expand the investigation to the effects of different social and moral attitudes on people's environmental preferences based on DCE.

Chapter 3

Exploring Different Assumptions about Outcome-Related Risk Perceptions in Discrete Choice Experiment

3.1 Introduction

In most discrete choice experiment (DCE) studies, policy outcomes associated with environmental goods are generally presented as certain (Roberts et al., 2008). Yet, when policies are implemented, outcome delivery is unlikely to be certain, and this is especially true when environmental outcomes are affected by the stochastic nature of the environment and ecosystems (Torres et al., 2017). Further uncertainty arises from the environmental policies themselves, as social, political and economic factors may influence the effectiveness of the policy, the subsequent effects on human behaviour and hence the environmental outcome (Rolfe and Windle, 2015). Failing to account for outcome uncertainty may not only result in biased WTP estimates (Cameron, 2005), but also make the scenario seem unrealistic to DCE respondents (Wielgus et al., 2009; Glenk and Colombo, 2011), posing a challenge to the external validity of the experiment.

In the DCE literature, studies have investigated the effects of embedding the information about risk of outcome delivery on environmental preferences, with some including risk in the valuation scenarios, (implicitly) in the attributes or their levels (Wielgus et al. 2009; Torres et al., 2017; Bujosa et al., 2018), and others as an attribute (Roberts et al., 2008; Rigby et al., 2010; Glenk and Colombo, 2011, 2013; Akitar et al., 2012; Rolfe and Windle, 2015).

Classic economic theory on stated risk perception is based on the expected utility (EU) framework (Von Neumann et al., 1947). In this framework, individuals are assumed to combine the information on risk with the associated outcomes and calculate expected utility outcomes with linearly weighted probabilities (representing risk) in the process of decision-making. However, under prospect theory individuals may over- or under-weigh low and high probabilities, respectively (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Moreover, some studies report that respondents value a risky prospect lower than its worst outcome, suggesting a direct aversion to risk (also called “uncertainty effect”) rather than a probability-weighted outcome (Gneezy et al., 2006; Simonsohn, 2009). In the DCE literature where information on risk is conveyed directly as an attribute of a policy, a number of studies focus on respondents’ behaviour in risky situations with environmental goods being specified as improvements. Roberts et al. (2008) tested whether incorporating information on risk affected individuals’ environmental preferences. Under the assumption of expected utility theory, they embedded the information on risk together with environmental attributes in their uncertainty treatment, and compared it to a certain treatment without the explicit risk information. Higher WTP values for the environmental goods were found in the uncertainty treatment. The results are confirmed by Torres et al. (2017), yet not confirmed by Glenk and Colombo (2011) and Lundhede et al. (2015), who observe lower WTPs in the presence of outcome delivery uncertainty.

Nevertheless, most DCE applications in environmental valuation fail to investigate multiple possible behavioural assumptions when risk is incorporated in experimental scenario. Past studies have often rejected the premise that respondents behave according to expected utility theory and suggest that risk is considered according to prospect theory (Roberts et al., 2008; Wibbenmeyer et al., 2013; Hand et al., 2015; Dekker et al., 2016). Other studies only test a limited number of behavioural assumptions (Akitar et al., 2012; Lundhede et al. 2015; Williams and Rolfe, 2017), or assume that the information of risk is evaluated independently of the corresponding environmental attributes (Glenk and Colombo, 2011). Glenk and Colombo (2013) compared the performance of DCE model specifications following expected utility, prospect theory and direct risk aversion assumptions. Their results suggest that the simple additive-in-attribute specification under a direct risk aversion assumption performs the best statistically compared to models under other assumptions with linear or non-linear utility functions. Rolfe and Windle (2015) also compared a series of different utility specifications and found that respondents place value on an environmental attribute in addition to expected environmental outcomes, implying an underestimation of environmental values under standard expected utility theory. On the contrary, a number of studies reported that respondents ignore risk information altogether (Veronesi et al., 2014; Vondolia and Navrud, 2019). Overall, with such limited and mixed evidence, it is difficult to draw conclusions regarding which behavioural pattern individuals use to reach environmental decisions in risky scenarios.

Furthermore, existing DCE studies have failed to investigate whether respondents apply asymmetric behavioural rules to environmental gains versus losses. Prospect theory substantiates that the way individuals consider risk when goods are described as losses is different to situations when those goods are described as gains. When goods are described as a loss relative to a reference point, individuals are found to be risk seeking. The utility function is hence convex in the loss domain and concave in the gain domain, whereas under expected utility theory utility functions are always concave. Several experimental studies have confirmed the different risk preferences in the gain and loss domains for monetary goods (Abdellaoui, 2000; Abdellaoui et al., 2005; Harrison and Rutström, 2009), as well as environmental good (Riddel et al., 2012). Such findings suggest that individuals' risk perceptions may differ between the gain and loss domains, and assuming symmetry in outcome-related risk perceptions could bias estimated values.

This is the first study that compares models following different behavioural rules in risky scenarios that cover both environmental gains and losses. This chapter aims to extend the investigation of outcome-related risk perceptions [36] in choices for environmental policies to both the gain and loss

[36] I use the term "outcome-related risk perceptions" to indicate the ways respondents understand and incorporate the risk information in decision-making. I acknowledge that "risk preferences" maybe a more accurate term in this context, but I do not use it to avoid any suggestion that this study aims to elicit risk preferences.

domains. Risk is incorporated as an attribute to represent the probability of the health outcomes under air pollution policies, and the health outcomes are defined as changes in annual hospital admissions due to air pollution in Beijing, China. Our design presents the health outcomes as future improvements or deteriorations from the current health level under risk, allowing us to investigate the ways in which respondents perceive outcome-related risk and whether respondents apply asymmetric behavioural rules between the gain and loss domains by comparing the statistical performance and the consistency between behavioural assumptions and parameter estimates of different model specifications. Results suggest that the elicited behavioural patterns are better described by the direct risk aversion theory in both the gain and loss domains, which states that people obtain disutility directly from the increasing risk itself regardless of the associated goods (Gneezy et al 2006; Simonsohn, 2009). Moreover, respondents are found to place different weights on the risk attribute between the gain and the loss domains. Further results from a posterior analysis suggest that ignoring the risk attribute and the self-reported opinion that deteriorating air quality is unacceptable significantly affect the asymmetry in outcome-related risk perceptions.

Section 3.2 presents a literature review of incorporating risk in DCE. Section 3.3 demonstrates the survey and experimental design of this chapter. Section 3.4 presents the modelling framework of this study followed by results in Section 3.5. Section 3.6 discusses the results and implications, and Section 3.7 provides the conclusion of this chapter.

3.2 Literature review

There are mainly three strands of DCE literature looking at the effects of uncertainty on individual preferences for environmental goods. First, uncertainty emerges from the effects of prior subjective assumptions about the likelihood of public good provision. These studies focus on how subjective perceptions about risk affect preferences for environmental goods and whether or not respondents update their prior risk perceptions when new information is provided (Cameron, 2005; Riddel and Shaw, 2006; Watanabe et al., 2017; Cerroni et al., 2019).

A second strand focuses on decision uncertainty (or preference uncertainty) which arises from the observation that individuals often feel uncertain about the choices they made. Decision uncertainty could emerge from unfamiliarity with public goods or no prior purchasing experience, leading respondents to make random choices, and thus biasing WTP estimates (Lundhede et al., 2009; Brouwer et al., 2011; Dekker, 2016). Incorporating self-reported choice certainty in the experiment, however, is found to be a way to calibrate preferences, welfare estimates and even hypothetical bias (Kosenius, 2010; Ready et al., 2010; Mattmann et al., 2019).

Finally, a third strand of literature is concerned with the effects of incorporating risk on environmental preferences. In these studies, there are generally two ways to embed the information on risk in a DCE: a) risk is given as a part of the valuation scenarios or as a range (Wielgus et al. 2009; Bojusa et al., 2018); risk is embedded in or as an attribute directly in the DCE (Roberts et al. 2008; Rigby et al. 2010; Glenk and Colombo, 2011, 2013; Akitar et al., 2012; Rolfe and Windle, 2015; Torres et al., 2017; William and Rolfe, 2017; Faccioli et al., 2019; Cerroni et al., 2019).

Wielgus et al. (2009) incorporated risk by stating the probability of occurrence in a valuation scenario, and also by using ranges, instead of fixed-values, to represent levels in attributes. They found the goodness of fit of the model decreases when attribute levels were treated as ranges, which could be the result of increased cognitive burden. They also found that embedding the information of risk in valuation scenario increases model fit, and this could be attributed to the enhancement of the survey credibility.

An early attempt by Roberts et al. (2008) aims to find whether incorporating risk affects individuals' environmental preferences. The information about risk in their study was integrated with environmental outcomes in an attribute in an uncertainty treatment, and individuals' environmental preferences of this treatment were compared with those in a certain treatment where risk is absent. Under the assumption of expected utility theory, they find higher WTP values for the uncertainty treatment than those for the certain treatment, and claim that enhanced scenario realism and subjective risk perceptions may contribute to the WTP differences. Yet, the result is reversed in Lundehede et al. (2015), in which WTP is reduced when moving from a certain to an uncertain outcome. Using treatment comparison (i.e., comparison between estimates in a certain and an uncertain treatment), Torres et al. (2017) also find a higher WTP for the uncertain treatment than the certain treatment, yet the WTP does not vary between two uncertain treatments with varying degrees of risk. They attribute this insignificant finding to the small difference between the two probabilities used. In general, despite that some evidence has shown significant level of risk effect, there is no consensus on the existence and the direction of the effect due to differences in experimental design.

In other studies, William and Rolfe (2017) investigate the effects of various sources of uncertainty on WTP. In the context of emission reduction, the source of risk is described as either from effectiveness of domestic policy measures or from the extent of international participation. Using between-sample comparisons, they find that respondents' WTPs differ according to the source of risk. Additionally, unlike most studies where outcome uncertainty is embodied in binary-outcome scenarios (i.e., risky scenarios where there is a probability to achieve an outcome and the rest of the probability to achieve another outcome), Makriyannis et al. (2018) find WTP difference between a sample where policy outcome is described as binary-outcome scenarios and another sample where multiple outcomes can be achieved.

A few studies focus on applying different utility specifications to incorporate outcome-related risk perception in DCE and underlining their corresponding behavioural implications. Some studies find that respondents' risk perception is more consistent with the prospect theory (PT) in which subjective weights are placed on outcome probabilities, unlike the widely-used expected utility (EU) theory assumption where respondents perceive the probabilities as they are (Roberts et al., 2008; Wibbenmeyer et al., 2013; Hand et al., 2015; Dekker et al., 2016). However, results differ according to the magnitude of probability distortion, with Roberts et al. (2008) and Dekker et al. (2016) substantiating an underestimation on small probability and an overestimation on large probability (i.e., an S-shaped weighting function), whilst Hand et al. (2015) finding an inverse S-shaped weighting function.

Glenk and Colombo (2013) contribute the first DCE study that systematically compares various model specifications with different behavioural implications in risky scenarios. An EU specification was compared with a PT or a direct risk aversion (DU) specification where risk was assumed to be separate with its corresponding environmental outcome. Additionally, specifications with assumptions of both linearity and non-linearity in attributes were tested under the EU and PT assumptions. Results suggest that the independent risk specification under the DU assumption has the best statistical performance compared with models under other assumptions. The main behavioural implication of the DU assumption is related to the direct risk aversion behaviour mentioned in Simonsohn (2009) and uncertainty effect mentioned in Gneezy (2006); these results imply that individuals may have direct distaste towards risk, regardless of the associated outcomes. DU behaviour has been confirmed in other contexts (Newman and Mochon, 2012), whereas it also has been questioned for the reason that respondents may have misunderstood the experimental instruction (Keren and Willemsen, 2009). Other explanations include insufficient cognitive load (Wang et al., 2013) and aversion to weird transaction features (Mislavsky and Simonsohn, 2018). In another DCE study, the model fit under the DU assumption is found to be similar to those under other specifications (Lundhede et al., 2015). Rolfe and Windle (2015) compared the model fit of an expected utility specification with those of a number of partial expected utility specifications where apart from the expected outcomes, respondents were assumed to place additional values on either the environmental or risk attribute. Results show that a partial expected utility specification with additional environmental values has the best model fit among all specifications, implying that individuals not only consider the expected environmental outcomes, but assign additional utility to the importance of the environmental good itself irrespective of the risk. In some other studies, risk is reported to have been ignored by respondents (Veronesi et al., 2014; Vondolia and Navrud, 2019), and cognitive burdens and education levels may explain the absence of the risk effect. Overall, Glenk and Colombo (2013), Lundhede et al. (2015) and Rolfe and Windle (2015) not only confirm that respondents take risk into account, but also take a further step to unveil different behavioural patterns respondents may apply in risky choices.

However, none of these studies investigate asymmetric outcome-related risk perception, yet findings from prospect theory and other lab or field experiments underline the asymmetric pattern of risk preferences between monetary gains and losses (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Abdellaoui, 2000; Abdellaoui et al., 2005; Harrison and Rutström, 2009).

To my best knowledge, there is only one DCE study that investigates the effects of risk in a context where either environmental improvements or deteriorations may occur in the future (Faccioli et al., 2019). However, the main research objective in their study is to investigate the effects of presenting risk on individuals' environmental preferences, while in this study, emphases are placed on the investigation of the behavioural rules that respondents apply in making choices under risk. In addition, as the information about risk in their experiment is stated in the description of the environmental attribute, and it does not vary independently across policy alternatives, rendering it impossible to test model specifications under alternative economic assumptions for risky choices.

To sum up, despite the fact that some efforts have been made to explore the effects of risk on individuals' preferences for environmental improvement, only a limited number of studies attempt to investigate the behavioural rules respondents apply in decision making under risky scenarios for environmental improvement. In additional, prospect theory implies that outcome-related risk perceptions may be different according to whether the future environmental scenarios are stated as improvement or deterioration, yet in DCE studies, no work has attempted to investigate different behavioural rules between the gain and loss domain.

3.3 Data and Experimental Design

The study area is Beijing, China, where air pollution has been heavy for years and raised public concerns since 2013. Outdoor air pollution annually causes 350,000-500,000 deaths in China (Chen, Wang, et al., 2013). Although policies have been implemented to combat the pollution problems, China's electricity generation still heavily relies on the coal industry. Thus, from a policy perspective, the government has to balance economic growth and air quality improvement.

Additionally, as environmental outcomes are probabilistic and predictions are estimates, risk and uncertainty play important roles in preference elicitation in the context of air pollution. First, the effects of air pollution on human health are not homogenous. The health complications of air pollution can be condition-specific, while heterogeneous individual behaviours will further influence the effects of air pollution on individual and public health outcomes. Second, the level of air pollution is affected by unpredictable weather conditions (Sario et al., 2013; Jhun et al., 2015). For example, rain reduces particulate matter (PM) concentrations and sunshine exaggerates ground-level ozone pollution (Li et al., 2019). Thus, realistic elicitation mechanisms must account for both air quality improvement and deterioration scenarios, as well as risk in health outcomes.

Attributes were selected according to the DCE literature on outdoor air pollution, expert consultation and results from questionnaire pre-tests. Four attributes were finally selected for this chapter: health, chance of success (only applied to health), visibility and cost.

The health attribute is represented by hospital admissions due to air pollution, a common health consequence of air pollution. In order to understand individuals' decision-making process in risky situations, I incorporate a risk attribute that describes the probability of the health outcomes that will come to fruition. Respondents were told that health outcomes are probabilistic due to limited scientific knowledge about the effect of air pollution on health. A step-by-step description about the concept of probability was then provided, with the underlying health outcomes of both scenarios (i.e., the health outcomes in case of success or failure) being explicitly explained. Specifically, respondents were told that health outcome would remain at the current health level, if the specified health improvement/deterioration did not occur. Respondents were then shown an example of what a "90% chance of success" means in the hypothetical context, and a bar graph was used as a visual aid to improve understanding of the probabilities. To make the hypothetical scenario more convincing and enhance respondents' comprehension that the probability is only applied to the health attribute, a short introduction was embedded in the survey. The introduction describes the scientific rationale behind the unpredictable nature of air pollution and its health effects

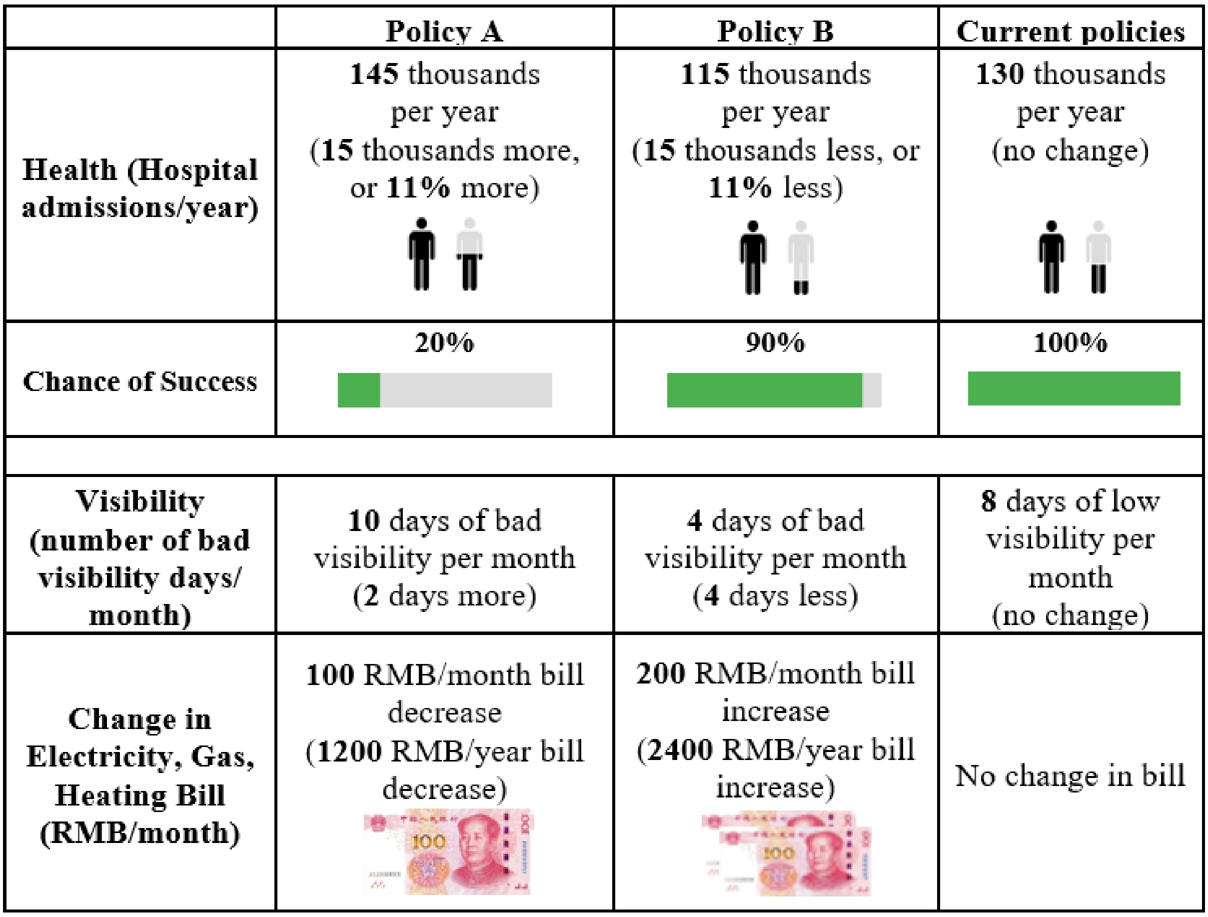
I use the number of "bad visibility days" in Beijing to represent the effect of visibility caused by air pollution. The cost attribute is formatted as the changes of the household electricity, gas and central heating bill, which is frequently used to support environmental services in China (Sun et al., 2016). Most citizens in Beijing pay electricity and gas bills. A central heating system covers most of the areas in Beijing and provides heating from mid-November to mid-March, with the bills being paid on an annual basis. The government can use the money collected from the energy bills to impose cleaner technology on targeted heavy-polluted industries to improve their environmental performance. In the hypothetical scenarios, households were asked to pay for the improvement of either health or visibility, or both; they could also be told to accept a bill reduction (as a monetary compensation) for a deteriorated air quality. The payment levels were repeatedly pre-tested and adjusted according to respondents' feedback.

The final attributes and their levels are presented in Table 3.1. An example of the choice card that was presented to respondents is given in Figure 3.1.

Table 3.1 Attributes and levels (Chapter 3)

Attributes	L-3	L-2	L-1	Current Situation	L1 [a]	L2	L3
Health effect (1000 hospital admissions/year)	150	145	140	130	120	115	110
Chance of success	90%	50%	20%	100%	20%	50%	90%
Visibility effect (bad visibility days/month)	/	12	10	8	6	4	/
Change in electricity, gas and heating Bill (RMB/month)	500 RMB [b] decrease	300 RMB decrease	100 RMB decrease	No change in bill	100 RMB increase	200 RMB increase	500 RMB increase

Note: (a) L1, L2 and L3 are possible levels for environmental improvements (or bill increase for the cost attribute); L-1, L-2 and L-3 are possible levels for environmental deteriorations (or bill reduction for the cost attribute); Current Situation is the level of attributes under current air pollution implementation. (b) According to China National Bureau of Statistics, the deposable income per capita in 2017 in China is 25,974 RMB (£2,966).



	Policy A	Policy B	Current policies
Health (Hospital admissions/year)	**145** thousands per year (**15** thousands more, or **11%** more)	**115** thousands per year (**15** thousands less, or **11%** less)	**130** thousands per year (no change)
Chance of Success	**20%**	**90%**	**100%**
Visibility (number of bad visibility days/ month)	**10** days of bad visibility per month (**2** days more)	**4** days of bad visibility per month (**4** days less)	**8** days of low visibility per month (no change)
Change in Electricity, Gas, Heating Bill (RMB/month)	**100** RMB/month bill decrease (**1200** RMB/year bill decrease)	**200** RMB/month bill increase (**2400** RMB/year bill increase)	No change in bill

Figure 3.1 An example of a choice card (Chapter 3)

A D-efficient fractional-factorial design was constructed, with three blocks of ten choice sets using Ngene (version 1.2). In each choice set, two policy alternatives that vary in attribute levels were presented, together with a status quo alternative with current effects of air pollution as attribute levels.

After signing the consent forms, respondents were first given an introduction on the current situation of air pollution in Beijing, followed by a step-by-step description of the choice scenarios and a warm-up DCE question. They were then asked to complete the choice experiment and a set of post-experimental and socio-demographic questions. The survey was administered through an online system by a Chinese marketing company between July and August 2018 across different regions in Beijing. Registered respondents from Beijing in the survey system were randomly sampled.[37] In order to control for data quality, a minimum time of staying on a certain page was imposed so that respondents would spend sufficient time on reading the scenario description.

3.4 Modelling framework

3.4.1 Random utility model

Within a random utility framework (McFadden, 1974), respondents obtain utility from choosing alternative *i*:

$$U_{ni} = v_{ni} + \varepsilon_{ni} \tag{3.1}$$

where U_{ni} is the utility of individual *n* choosing alternative *i*. v_{ni} is the value function, i.e. the part of the utility observable to the researcher given by the DCE attributes, while ε_{ni} represents a stochastic component following some known distribution. Under certainty and symmetry in the gain and loss domains, the value function is specified as Equation 3.2, where H_{ni}, V_{ni} and C_{ni} are the health, visibility and cost attributes, respectively.

$$v_{ni} = \beta_H H_{ni} + \beta_V V_{ni} + \beta_C C_{ni} \tag{3.2}$$

Equation 3.2 can also be specified as asymmetric in the gain and loss domains for the health attribute, i.e. according to whether changes of health are stated as an improvement or deterioration. I only consider an asymmetric specification for the health attribute as only this attribute is subject to uncertainty in the scenario of this experiment; visibility and cost are not uncertain and assumed to

[37] Note that data collection of the three experiments in this thesis (i.e., the DCE in this chapter and the other two experiments mentioned in Chapter 2 and Chapter 4) was conducted in parallel, but each respondent was only allowed to attend one of the three experiments.

have linear and symmetric effects on individuals' utility. The specification is presented in Equation 3.3:

$$\mathrm{v}_{ni} = \beta_H^{imp} H_{ni}^{imp} + \beta_H^{det} H_{ni}^{det} + \beta_V V_{ni} + \beta_C C_{ni} \tag{3.3}$$

where H^{imp}= max(H_{SQ}−H, 0) indicates an improvement in health in alternative i relative to the reference point (i.e., the current health level), and H^{det} = max($H - H_{SQ}$, 0) indicates a deterioration in health relative to the reference point.

3.4.2 Research questions

3.4.2.1 Research Question 1: What is the best utility specification within the gain-loss framework under uncertainty?

The first objective is to identify the model specification that fits the data the best among all candidate specifications of value functions with different assumptions about risk perceptions.[38] Model selection is based on (a) statistical performance and (b) whether estimated parameters are consistent with their corresponding theoretical assumptions. BIC is used to evaluate relative statistical performance among different utility specifications. The J test (Davidson-MacKinnon, 1981) is used to provide additional evidence for non-nested model comparison.

(1) Direct risk aversion specification

The most straightforward way of incorporating risk is treating it as an independent (linear additive) attribute corresponding to the behavioural assumption of direct risk aversion (DU) (Gneezy et al., 2006; Simonsohn, 2009). In this specification, the risk attribute is evaluated independently of the associated health outcome. The model is specified as in Equation 3.4, where R_{ni}^{G} and R_{ni}^{L} represent the independent risk attributes in the gain and loss domains, respectively. Insignificant risk parameters would imply that respondents ignore the risk attribute in gain and loss domains.

$$\mathrm{v}_{ni} = \beta_R^G * R_{ni}^G + \beta_R^L * R_{ni}^L + \beta_H^{imp} H_{ni}^{imp} + \beta_H^{det} H_{ni}^{det} + \beta_V V_{ni} + \beta_C C_{ni} \tag{3.4}$$

(2) Expected utility specification

[38] I acknowledge that non-linear utility functions cannot be precisely estimated with the limited number of attribute levels in this study, but I can approximate different value functions corresponding to different underlying theoretical utility functions.

As past studies have found that respondents in DCEs may perceive risk according to expected utility theory (EU) (Glenk and Colombo, 2013; Rolfe and Windle, 2015), a value function approximating EU is specified as:

$$v_{ni} = \beta_{HR}^{imp}(H_{ni}^{imp} \times R_{ni}^{G}) + \beta_{HR}^{det}(H_{ni}^{det} \times R_{ni}^{L}) + \beta_V V_{ni} + \beta_C C_{ni} \tag{3.5}$$

where $H_{ni}^{imp} \times R_{ni}^{G}$ and $H_{ni}^{det} \times R_{ni}^{L}$ represent the interactions of the risk and health attributes in alternative *i* in the gain and loss domains, respectively. For the EU specification, it is expected that $\beta_{HR}^{imp} > 0$ and $\beta_{HR}^{det} < 0$. Parameter signs contradicting this expectation would imply that estimated parameters for this value function specification are not consistent with EU theory.[39]

A dummy-coded EU specification (i.e. where non-linear effects of health are examined) is also applied to understand the change of risk perceptions under different health levels, which is shown in Equation 3.6:

$$v_{ni} = D_{HR} HR_{ni} + \beta_V V_{ni} + \beta_C C_{ni} \tag{3.6}$$

where $\mathrm{HR}_{\mathrm{ni}}$ represents the dummy-coded interaction terms between the health and the risk attributes, and D_{HR} is a parameter vector for these interaction terms. Six health levels and three risk levels are considered in the experiment, resulting in 17 dummy-coded variables. In the regression, $\mathrm{P}^{20} \times \mathrm{H}^{11}$, which represents the health level of 110,000 hospital admissions with 20% chance to achieve this outcome, is treated as the reference level.

It is acknowledged that a non-linearity effect of health on utility is normally assumed under the EU assumption. For simplicity, linear health effect is assumed in the main analysis, but more complicated non-linear effect will be tested in Appendix B.1.

(3) Prospect theory specification

Prospect theory (PT) (Kahneman, 1979) states that people over-weight small probabilities and under-weight large probabilities (i.e., a specific type of risk non-linearity). According to Abdellaoui et al. (2005) and Booij et al. (2010), weighting functions may be different in the gain and loss domain, as

[39] I also notice that if β_{HR}^{imp} (or β_{HR}^{det})=0, this may mean that not the risk attribute (according to EU theory), but the health attribute is ignored. Therefore, I test whether respondents consider the health attribute in their choices by adding two additional health attribute terms and evaluating the statistical significance of the coefficients. Significant coefficients with a theoretically valid sign indicate that the health attribute is not ignored by respondents.

people may have different risk perceptions between the two domains. The corresponding value function is given in Equation 3.7:

$$v_{ni} = \beta_{HW}^{imp}[W^{+}(R_{ni}^{G}) \times H_{ni}^{imp}] + \beta_{HW}^{det}[W^{-}(R_{ni}^{L}) \times H_{ni}^{det}] + \beta_{V}V_{ni} + \beta_{C}C_{ni} \tag{3.7}$$

where $W^{+}(\cdot)$ and $W^{-}(\cdot)$ represent the weighting functions in the gain and loss domains, respectively. For the weighting function specification, I choose two functional forms proposed by Tversky and Kahneman (1992) and Prelec (1998), which are frequently used in applications of prospect theory (Wibbenmeyer et al., 2013; Hand et al., 2015):

$$W(\mathrm{p}) = \frac{p^{\Upsilon}}{[p^{\Upsilon}+(1-p)^{\Upsilon}]^{1/\Upsilon}} \tag{3.8}$$

$$W(\mathrm{p}) = e^{[-(-\ln(p))^{\theta}]} \tag{3.9}$$

where p is the probability representing the risk attribute. In Equation 3.8, Υ is the probability weighting parameter, where $\Upsilon \in (0,1]$ denotes the degree of curvature. For $\Upsilon = 1$, $W(\mathrm{p}) = \mathrm{p}$ implies a linear weighting function, while $\Upsilon \in (0,1)$ implies an inverse-S shape weighting function, denoting that people generally over-weight small probabilities and under-weight medium and large probabilities. In Equation 3.9, $\theta \in (0,1]$, with the weighting function collapsing to a linear probability weighting when $\theta = 1$. Estimates for the weighting function parameters can be obtained through a grid search. Overall, empirical values of $\Upsilon < 1$ and $\theta < 1$ would suggest that respondents in the dataset treat probabilities non-linearly. It is acknowledged that a non-linearity effect of health on utility is normally assumed under the PT assumption. For simplicity, linear health effect is assumed in the main analysis, but more complicated non-linear effect will be tested in Appendix B.1.

3.4.2.2 Research Question 2: Are risk effects in the gain and loss domain asymmetric?

Research Question 2.1: Do respondents impose different behavioural rules in the gain and loss domains?

In attributes trade-off, respondents may impose different behavioural rules in the two domains. For example, respondents may consider risk according to EU theory or PT in the gain domain, but according to DU behaviour in the loss domain. The corresponding value functions for these two domain-asymmetric models according to the EU and PT in the gain domain and DU in the loss domain are:

$$v_{ni} = \beta_{HR}^{imp}\left(H_{ni}^{imp} \times R_{ni}^{G}\right) + \beta_{H}^{det}H_{ni}^{det} + \beta_{R}^{L} * R_{ni}^{L} + \beta_{V}V_{ni} + \beta_{C}C_{ni} \tag{3.10}$$

$$v_{ni} = \beta_{HW}^{imp}[W^{+}(R_{ni}^{G}) \times H_{ni}^{imp}] + \beta_{H}^{det}H_{ni}^{det} + \beta_{R}^{L}R_{ni}^{L} + \beta_{V}V_{ni} + \beta_{C}C_{ni} \tag{3.11}$$

To answer this research question, I compare the statistical performance of the two models with the model that performs the best in Research Question 1.

Research Question 2.2: For the model with the best statistical performance, are risk effects in the gain and loss domain of similar magnitude?

I explore whether respondents place equal importance to the risk attribute in both domains by testing whether the mean parameter of the risk attribute in the gain domain is significantly different from the one in the loss domain for the statistically superior model obtained in Research Question 1. For example, if the DU specification has the best model fit, then in Equation 3.4, $\beta_R^G \neq \beta_R^L$ could be seen as evidence that respondents place asymmetric importance on risk in the two domains.

3.4.3 Econometric models

In the various model specifications, when assuming an IID error term (ε_{ni}) following an extreme value type I distribution, McFadden's conditional logit is obtained (McFadden, 1974). Yet, the IID assumption of the error term is often violated in empirical analyses, implying a lack of preference homogeneity across respondents or correlation across alternatives. I model unobserved preference heterogeneity through a mixed logit model (Hensher and Greene, 2003), where an attribute parameter is decomposed to a fixed and a random component following a pre-assumed distribution.

Models are run in Stata 15 (through the -mixlogit- routine (Hole, 2007)) and R v.3.6.0 (through codes provided by Choice Modelling Centre (Choice Modelling Centre, 2017)) based on 500 Halton draws for random parameters. Random parameters are assumed to be normally distributed. As robustness checks, other distributional assumptions and higher random draws are also tested, and the details are reported in Appendix B.1.

3.4.4 Posterior analysis

Through posterior analysis, I explore how individual characteristics relate to asymmetry in risk perceptions, which may provide further insights into the risk perceptions in the gain and loss domains across social groups. I regress the individual conditional means of the risk parameters extracted from the DU model on individual socio-economic factors, an environmental attitude variable (i.e., acceptance of air quality deterioration scenarios) and a self-reported attribute non-attendance variable (i.e. a self-reported ignoring attribute in decision-making).

3.5 Results

3.5.1 Descriptive statistics

Summary statistics for the sample are given in Table 3.2. The sample characteristics are not significantly different from the general population of Beijing for the gender and income variable, but the sample tends to be better educated and younger. This is potentially due to the use of web-based experiment where selected respondents must have online access and a registered account with the marketing company.[40] Of those who completed the survey, those who had no variation in their DCE answers (i.e., always choose Policy A or Policy B) are excluded, which account for 1.7% (6 subjects) of the whole sample. Therefore, 339 respondents are included in the DCE analysis.

[40] I acknowledge that a younger and more educated sample implies that people in the sample may have a better understanding about risk and have higher cognitive ability, and are therefore less likely to apply heuristics in decision making than those among the general public in Beijing.

Table 3.2 Summary statistics of respondent characteristics

Variables	**Sample**	**General population** [c]
Age		
18-25 years	6.1%	21%
25-35 years	38.8%	23%
35-45 years	44.6%	19%
45-55 years	9.9%	18%
>55 years	0.6%	20%
Gender (male %)	49.9%	51.2%
Highest level of education completed		
High school or lower	8.7%	67%
Undergraduate	86.1%	29%
Postgraduate or higher	5.2%	4%
Annual gross income per person (RMB)		
80,000 or less	7.5%	
80,000-200,000	61.7%	
200,000-300,000	24.9%	
300,000 or higher	5.8%	
Mean income [a]	171,930	113,073
Responsible for bill [b]	92.8%	
Sample size	345	

Note: (a) The mean of income for the sample is represented by weighted sum of means of each income category; (b) Responsible Bill is the Self- reported responsibility for the household bill (Yes/No). (c) Age and education data for the general population are from the 2010 Population Census of China, and gender and income data are from the Beijing Statistical Yearbook 2017.

3.5.2 Estimation results

Estimation results are given in Table 3.3. For the No Risk specification (model 1), health, visibility and cost variables are all significant at a 5% level with expected signs. More "bad visibility days", more hospital admissions due to air pollution and higher cost all lead to higher disutility, while fewer hospital admissions increase utility. A negative coefficient for the status quo alternative indicates a tendency to opt for the proposed new policies rather than staying with the current policies, which is consistent with Yao et al. (2019). In addition, significant standard deviations of the random variables for the health, visibility and risk attributes in most model specifications suggest the presence of preference heterogeneity in the sample.[41]

For Research Question 1, the model that does not include risk (No Risk, model 1) is compared with the model that considers risk according to the direct utility assumption (DU, model 2), the expected utility model (EU, model 3) and the prospect theory model (PT, model 4). Firstly, significant risk coefficients in both the gain and loss domains are observed for all risk models, suggesting that individuals incorporate risk in their decision-making. Secondly, the parameters in the DU model (model 2) are found to have signs consistent with the DU assumptions. For the EU model (model 3), the results of the dummy-coded specification (Table 3.4) reveal that for the same health level, utility in the gain domain is generally increasing as the probability increases, which is in line with EU assumption. However, inconsistent with the EU assumption, utility in the loss domain increases as the probability increases. The counter-intuitive preference for risk in the loss domain provides evidence that respondents neither make decisions according to EU theory, and by extension nor by PT theory, in which probabilities are non-linearly weighted. In the PT specification, I therefore only apply PT assumptions in the gain domain, combined with a DU specification in the loss domain. In summary, I find that the parameters in EU and PT models do not conform to their corresponding theoretical assumptions. Finally, the comparison of the model fit suggests that the DU specification (model 2) has the smallest BIC value, which is consistent with findings from Glenk and Colombo (2013). Additionally, a series of robustness checks have been conducted and the results are consistent with the

[41] I acknowledge that for most random parameters in the mixed logit model estimation, the standard deviations of variables are larger than the means, implying that a number of respondents locate to an area in distribution where the signs of the individual parameters contradict to the mean. In an analysis that is not reported in this study (available upon request), I investigate the determinants of sign violation by regressing the dummy variables of the conditional means of the risk attributes on individual characteristics. The dummy variable equals to 1 if the individual-level conditional means have signs consistent with the unconditional mean, and equals to 0 if the conditional means have reversed signs. Results suggest that although most individual characteristics do not have significant effects, self-reported non-attendance of the risk attribute is positively correlated with sign violations of the risk attribute in the gain domain. In the loss domain, age and education negatively affect sign violations of the risk attribute, whilst the effect for the self-reported difficulty of the survey is positive. These results imply that some individual characteristics and the complexity of the experiment may play roles in respondents' understanding of the experiment.

finding that DU outperforms other specifications (see Appendix B.1 for details).[42]

For Research Question 2.1, I test whether the models with a EU or PT specification in the gain domain and a DU specification in the loss domain conform to the corresponding theoretical assumptions and whether they outperform the model with the best statistical performance in Research Question 1 (i.e. the DU specification in both domains). The key results are shown in models (4) and (5) in Table 3.3 (further specifications and results are reported in section B.1.4 in Appendix B.1). The attribute coefficients for the EU (gain)-DU (loss) (model 5) and PT (i.e., model 4) are consistent with their corresponding theoretical assumptions. For the PT model, the Υ parameter is 0.51, implying an inverse S-shaped probability weighting function, in which the small probability (20%) is overestimated, whereas the medium and large probabilities (i.e., 50% and 90%) are underestimated.[43] This finding is consistent with Wibbenmeyer et al. (2013) and Hand et al. (2015) where respondents tend to distort probabilities when they evaluate environmental goods in risky scenarios. Figure B.1 in Appendix B.2 presents the plots of the weighting functions. While the explanatory power of the PT model is higher than that of the EU (gain)-DU (loss) model where linear probability weighting is assumed in the gain domain, the DU model outperforms both as measured by BIC values. To sum up, the results suggest that respondents do not apply different behavioural rules between the gain and loss domains, and that the DU specification in both domains fits the data the best.

Moving onto Research Question 2.2, I test whether respondents place equal importance on the risk factor in the gain and loss domains. In the DU specification (model 2 in Table 3.3), significant difference between the mean parameters of the risk attribute in the gain and the loss domains are found using the Wald test (p-value = 0.01), implying asymmetrical magnitude of risk perception between the gain and loss domains.

[42] I acknowledge that WTP and WTA estimates will provide evidence that are more policy relevant, although the results of preference estimates presented in the results sections alone can answer the research questions/hypotheses in Chapter 3 and later on in Chapter 4. However, I do not present monetary estimates in the results sections, as the estimated cost parameter in the loss domain is insignificant, and hence the WTA estimates are not calculable. Different model specifications have been tested (e.g., imposing different distributional assumptions on the monetary parameter, allowing for correlation between random parameters, etc.), yet the cost parameter in the loss domain either remains insignificant, or becomes negatively significant, contradicting my expectation. Section 5.2.2 provides further analysis regarding respondents' insensitivity towards the change of the cost attribute in the loss domain, and the results suggest that taboo trade-off aversion and attribute non-attendance to bill reduction, which explain the insignificant cost parameter in Chapter 2, also explain the counterintuitive results relating to the monetary attribute in Chapter 3 and Chapter 4. This suggests that moral concern may play a role across all experiments in this thesis, and further research is needed to understand the formation of moral consideration in DCE and its effects on welfare estimates.

[43] Testing Prelec's (1998) one-parameter weighting function produces comparable results where small probabilities are overestimated and large probabilities are underestimated, while a similar fit is observed (BIC = 6011).

Table 3.3 Results of mixed logit models for different utility specifications

Variables [b]	(1) No Risk [a]	(2) DU	(3) EU	(4) PT	(5) EU (gain)-DU (loss)
Cost	-0.0005***	-0.0004***	-0.0002**	-0.0004***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Random parameters (mean)					
ASC SQ	-1.254***	-2.712***	-0.716***	-1.770***	-1.837***
	(0.175)	(0.257)	(0.147)	(0.232)	(0.225)
Visibility	-0.124***	-0.125***	-0.097***	-0.136***	-0.131***
	(0.017)	(0.017)	(0.016)	(0.018)	(0.017)
$\mathrm{H^{imp}} \times \mathrm{R^G}$			0.011***		0.007***
			(0.001)		(0.001)
$\mathrm{H^{imp}} \times \mathrm{W(R^G)}$				1.259***	
				(0.166)	
$\mathrm{H^{det}} \times \mathrm{R^L}$			-0.010***		
			(0.002)		
$\mathrm{H^{imp}}$	0.432***	0.376***			
	(0.094)	(0.105)			
$\mathrm{H^{det}}$	-1.089***	-0.920***		-1.244***	-1.405***
	(0.140)	(0.144)		(0.152)	(0.157)
$\mathrm{R^G}$		0.014***			
		(0.002)			
$\mathrm{R^L}$		0.007***		0.006***	0.005***
		(0.002)		(0.002)	(0.002)
Standard deviations of random parameters					
ASC SQ	1.831***	1.148***	2.048***	1.820***	1.862***
	(0.160)	(0.201)	(0.157)	(0.173)	(0.208)
Visibility	0.221***	0.221***	0.193***	0.224***	0.218***
	(0.019)	(0.019)	(0.018)	(0.020)	(0.019)
$\mathrm{H^{imp}} \times \mathrm{R^G}$			0.193***		0.009***
			(0.001)		(0.001)
$\mathrm{H^{imp}} \times \mathrm{W(R^G)}$				1.474***	
				(0.220)	
$\mathrm{H^{det}} \times \mathrm{R^L}$			0.023***		
			(0.003)		
$\mathrm{H^{imp}}$	0.858***	1.013***			
	(0.104)	(0.101)			
$\mathrm{H^{det}}$	1.745***	1.580***		1.938***	1.959***
	(0.140)	(0.138)		(0.144)	(0.147)
$\mathrm{R^G}$		0.020***			
		(0.002)			
$\mathrm{R^L}$		0.008***		0.011***	0.012***
		(0.002)		(0.002)	(0.002)
Weighting function parameter					
ϒ				0.51	
Model statistics					
BIC	6056	5957	6248	6012	6019
McFadden R^2	0.147	0.159	0.122	0.151	0.151
n(observations) [d]	10,170	10,170	10,170	10,170	10,170

Notes: (a) No risk is the model without the risk variable, DU is the direct risk aversion specification, EU is the expected utility specification, PT is the prospect theory specification and EU (gain)-DU (loss) is the specification with expected utility specification in the gain domain and direct risk aversion in the loss domain. (b) ASC SQ is the alternative specific constant for the "current policies" (status quo) option; $\mathrm{H^{imp}}$ ($\mathrm{H^{det}}$) is the health attribute in the gain (loss) domain; $\mathrm{H^{imp}} \times \mathrm{R^G}$ ($\mathrm{H^{det}} \times \mathrm{R^L}$) is the interaction term between the health and risk attributes in the gain (loss) domain; $\mathrm{H^{imp}} \times \mathrm{W(R^G)}$ is the interaction term between the health attribute and the probability weighting function in the gain domain; $\mathrm{R^G}$ ($\mathrm{R^L}$) is the risk attribute in the gain (loss) domain; Visibility is the visibility attribute; Cost is the cost attribute. (c) Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. (d) Number of observations is calculated according to the total number of choices times the number of alternatives instead of the conventional measure of the number of observations, due to the data structure of Stata.

Table 3.4 Results of mixed logit model with a dummy-coded expected utility specification

Variables [a]	Mean	S.D.
Cost	-0.0004***	
	(0.0002)	
Random parameters		
ASC SQ	-1.784***	2.283***
	(0.203)	(0.154)
Visibility	-0.139***	0.277***
	(0.022)	(0.027)
$P^{20} \times H^{11.5}$	0.009	-0.432
	(0.221)	(0.434)
$P^{20} \times H^{12}$	-0.764***	1.154***
	(0.216)	(0.418)
$P^{20} \times H^{14}$	-2.184***	0.105
	(0.241)	(0.517)
$P^{20} \times H^{14.5}$	-2.476***	-1.719**
	(0.351)	(0.699)
$P^{20} \times H^{15}$	-3.899***	5.634***
	(1.178)	(2.009)
$P^{50} \times H^{11}$	0.146	2.766**
	(0.308)	(1.093)
$P^{50} \times H^{11.5}$	0.281	1.497***
	(0.231)	(0.383)
$P^{50} \times H^{12}$	0.0515	0.249
	(0.172)	(0.379)
$P^{50} \times H^{14}$	-1.690***	-0.214
	(0.248)	(0.497)
$P^{50} \times H^{14.5}$	-2.674***	1.187***
	(0.297)	(0.385)
$P^{50} \times H^{15}$	-2.107***	0.592*
	(0.227)	(0.337)
$P^{90} \times H^{11}$	0.663**	1.108***
	(0.262)	(0.383)
$P^{90} \times H^{11.5}$	0.849***	-1.832***
	(0.250)	(0.541)
$P^{90} \times H^{12}$	0.278	3.517***
	(0.326)	(0.847)
$P^{90} \times H^{14}$	-1.530***	0.608
	(0.232)	(0.570)
$P^{90} \times H^{14.5}$	-1.735***	0.777**
	(0.240)	(0.351)
$P^{90} \times H^{15}$	-2.558***	2.019***
	(0.354)	(0.607)
Model Statistics		
McFaddenR^2	0.105	
BIC	6550	
n(observations) [c]	10,170	

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; Visibility is the visibility attribute; Cost is the cost attribute; $P^n \times H^m$ is the dummy coded interaction terms between the health and risk attributes, where n=20,50 or 90 and m=11,11.5,12,14,14.5 or 15. $P^{20} \times H^{11}$ is omitted in the regression as it is the base level of the dummy variables. (b) Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; (c) Number of observations is calculated according to the total number of choices times the number of alternatives instead of the conventional measure of the number of observations, due to the data structure of Stata.

To explore whether individual characteristics, cognitive burden and environmental attitudes affect outcome-related risk perceptions in the gain and loss domains under the DU assumption, a posterior analysis is conducted and the results are presented in Table 3.5. Findings suggest that self-reported non-attendance to the risk attribute and unaccepting the scenarios of air quality deterioration play significant roles. Respondents who reported that they did not ignore the risk attribute have larger risk coefficients in the gain domain. An effect of ignoring the risk attribute on risk coefficient is not detected in the loss domain, but respondents who reported to have ignored the risk attribute had lower degree of asymmetry in outcome-related risk perceptions than others. Additionally, in model (3) those who found air quality deterioration scenarios unacceptable show a larger asymmetry in outcome-related risk perceptions.

Table 3.5 OLS regressions of conditional means of risk attribute on various individual characteristics (under the direct risk aversion assumption)

Variables [a]	**(1) Conditional means (gain)**	**(2) Conditional means (domain)**	**(3) Difference of conditional means**
Survey difficulty			
Very easy	-0.009***	-0.002***	-0.007***
	(0.003)	(0.001)	(0.003)
Easy	-0.003	0.000	-0.003
	(0.002)	(0.001)	(0.002)
Difficult	-0.001	0.001	-0.002
	(0.002)	(0.001)	(0.002)
Very difficult	0.003	0.000	0.003
	(0.003)	(0.001)	(0.003)
Ignore risk	-0.006***	-0.000	-0.055**
	(0.002)	(0.001)	(0.021)
Not accepting air deterioration	0.007***	0.001**	0.006***
	(0.002)	(0.000)	(0.001)
Income [c]	0.008	-0.003	0.011
	(0.010)	(0.003)	(0.010)
Age [c]	0.006	0.003	0.003
	(0.010)	(0.003)	(0.010)
Education	-0.000	0.000	-0.000
	(0.002)	(0.000)	(0.002)
Responsible for bill	-0.006	0.000	-0.006*
	(0.002)	(0.001)	(0.003)
Constant	0.017	0.006***	0.011
	(0.009)	(0.002)	(0.009)
Model statistics			
n(observations)	339	339	339
R-squared	0.13	0.07	0.10

Notes: (a) Survey difficulty is the self-reported difficulty of the experiment from 1 (very easy) to 5 (very hard), and the base level in the regression is 3 (normal); Ignore risk is the self-reported ignoring of the risk attribute (equals 1 if a respondent stated to have ignored the risk attribute, and 0 if not); Not accepting air deterioration is the self-reported unacceptance of air quality deterioration scenarios (equals 1 if reported deterioration scenario is unacceptable, and 0 if acceptable); Income is a categorical variable that represents the midpoints of ranges of respondents' annual incomes (in RMB); Age is the averaged midpoints of the ranges of respondents' age (in year); Education is respondents' highest education level; Responsible for bill is the self-reported responsibility for the household bill (Yes/No). (b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. (c) Income and age are rescaled by 0.01 to facilitate reading, whilst the statistical performance of these variables remain unchanged.

3.6 Discussion

Incorporating uncertainty into DCEs has been claimed to increase the credibility of the experiment and mitigate the hypothetical bias of welfare estimates for environmental goods. Yet, despite attributes often being of uncertain nature, most DCEs in the literature fail to consider information about risk in their experimental design. Among the limited number of studies exploring respondents' outcome-related risk perceptions for environmental goods, with the exception of one (Faccioli, et al., 2019), all limit themselves to designs where environmental attributes are specified as improvements. Following many empirical findings of asymmetric outcome-related risk perceptions in other contexts, this study is the first to extend the investigation into both the gain and loss domains using a DCE (i.e. when the choice set may contain policy options where the environmental attributes are specified as either improvements or deteriorations). This design allows researchers to reveal the behavioural rules respondents apply in choices under risk and to test whether their risk perceptions are asymmetric between the gain and loss domains.

The results show that individuals take risk into account in decision making for environmental gains and losses. Compared with expected utility theory and its variations (i.e., partial expected utility specifications) and prospect theory, the elicited behavioural patterns are better described by the DU assumption, where people obtain disutility directly from the increasing risk, regardless of the associated good (Gneezy et al., 2006; Simonsohn, 2009). The results in the gain domain are consistent with findings from Glenk and Colombo (2013) who compared a series of different utility specifications and found a better model fit for the DU specification than the more conventional expected utility specification. In other DCE studies that have incorporated risk as an attribute, the model fit of the DU specification is either the same or slightly inferior to other candidate specifications (Lundhede et al., 2015; Rolfe and Windle, 2015). In the loss domain, results from a dummy-coded expected utility model indicate an increase in utility when the probability increases (holding the health levels constant), contrary to the assumptions of expected utility theory (i.e., a decrease in utility when the probability increases). This finding reinforces the argument that respondents behave according to the DU assumption.[44]

Moreover, respondents are found to place higher weight on the risk attribute in the gain domain than that in the loss domain under DU assumption. A possible explanation is that respondents consider that gambles have different levels of attractiveness between the two domains (Gonzalez and Wu, 1999).

[44] However, the model with DU assumption is not the best recommended specification in Glenk and Colombo (2013) due to the lack of theoretical support. It is acknowledged that evidence supporting the DU theory are far less than that for expected utility theory and prospect theory. Systematically exploring the reasons behind the DU decision making strategy is beyond the scope of this study, yet the results could provide insights to researchers in the DCE community on the experimental design when risk is incorporated.

In the scenarios of this experiment, a possible reason for a higher attractiveness of the gain domain is that respondents are more familiar with the gain than the loss scenarios, and thus averse to gambles on an unknown domain. This explanation can be supported by the results from Kilka and Weber (1998), who find that priced lotteries based on price changes of a familiar stock show greater attractiveness to respondents than an unfamiliar stock (also see Abdellaoui et al. (2011) for an up-to-date study discussing how the source of uncertainty affects willingness to bet).

Posterior analysis is used to assess the determinants of outcome-related risk perceptions under the DU assumption in the gain and loss domains, as well as the asymmetry in risk perceptions between the two domains. Results suggest that respondents who stated to ignore the risk attribute also put lower importance on risk in the gain domain. This may mirror findings in lab experiments where cognitive burden is shown to play a role in the DU behaviour (Wang et al., 2013). Additionally, not accepting air quality deterioration is found to significantly affect the asymmetric risk perceptions. A possible explanation is that trade-offs in the loss domain, where the environment is sacrificed in return for monetary compensation, trigger moral outrage or decision difficulties (Tetlock et al., 2000; Zaal et al., 2014; Daw et al., 2015), especially among respondents who find environmental losses unacceptable and therefore pay less attention to the loss than the gain domain.

Some limitations are acknowledged. Firstly, although incorporating risk as a separate attribute enables one to examine different utility specifications where outcome-related risk perceptions are assumed to affect choices differently, this design may lead respondents to treat risk separately from the associated environmental outcomes. Despite the fact that most existing DCE studies have embedded risk as an independent attribute, more research is needed to understand to what extent respondents are affected by this “attribute separation effect”. This may require alternative, flexible DCE designs to test different utility specifications, while minimizing the presentation effects of separate attributes. Additionally, I cannot rule out the possibility that due to the complexity of the experimental design, respondents may have experienced cognitive difficulty and used heuristics to process the information in the attributes and hypothetical scenarios, leading them to assess the associated risk levels in a more parsimonious way (Visschers, 2009). Recent research has found that heterogeneity in numeracy skills and knowledge about expected values explains part of the noise in risk preference studies (Dave et al., 2010; Taylor, 2016) and explains difficulties in comprehending risk information in DCE (Kjær et al., 2018). In the experiment, not all respondents may have had the necessary resources (e.g. a calculator) to compute the expected values of each choice, and hence may not have behaved strictly according to expected utility theory even if they wanted to. Therefore, those with lower numeracy skills may have treated risk as a stand-alone attribute irrespective of the associated environmental outcomes. Like most existing DCE studies, the information on expected outcomes is not provided, as I did not want to suggest respondents that they were supposed to behave according to expected utility theory.

Overall, this study extends the investigation of outcome-related risk perceptions to both the gain and loss domains and emphasizes the importance of using statistical methods to compare different utility specifications that have different implications about outcome-related risk perceptions in DCEs studies. For practitioners and applications where results are to be used in policy-making, expected utility theory, with its standard utility maximization assumption, may be a better model assumption for modelling DCE data when welfare effects need to be calculated. In such cases, researchers are recommended to design DCEs that facilitate an expected utility interpretation, and particularly focus on a clear, step-by-step description of the role of risk in the hypothetical scenarios to generate choice data and welfare estimates with meaningful policy implications (Visschers, 2009). On the other hand, use of flexible designs is recommended so that different ways in which respondents treat risk can be tested (where model fit criteria guide model choice) if the aim is to investigate the influence of risk on individual choice behaviour, and how risk can be included in DCE designs,.

3.7 Conclusion

The results reveal that respondents' elicited behavioural patterns are better described by direct risk aversion theory than by expected utility theory or prospect theory. Moreover, under the direct risk aversion assumption, an asymmetric pattern of risk perception is found for environmental gains and losses, and ignoring risk and refusing to accept air quality deterioration, contribute to this asymmetry. This chapter emphasizes the need to accommodate risk in the design of DCEs and the importance of accounting for asymmetric risk perceptions when future environmental outcomes could be either improved and deteriorated. The study also stresses the importance of cautiously designing the scenario description of the DCE to better elicit preference and welfare estimates that are meaningful in policy-making.

Chapter 4

The Effects of Risk on Individuals' Preferences for Air Quality—Evidence From a Discrete Choice Experiment

4.1 Introduction

Decision making that involves risk and uncertainty occurs in every aspect of social and economic life. Risk preferences, i.e. the extent to which people are willing to take risks, have been well documented in the economics literature using lab or field experiments for monetary goods. Under expected utility theory, people are risk averse, implying that subjects are willing to pay for risk reduction, in addition to the expected outcomes of the estimated goods (Von Neumann et al., 1947). Yet, under prospect theory assumptions (Tversky and Kahneman, 1992), a domain-specific risk preference pattern is assumed where respondents are risk averse for monetary gains and risk seeking for monetary losses. Additionally, results from prospect theory studies also substantiate probability-specific risk attitudes (or four-fold pattern of risk attitudes), where in the monetary gain domain, people are risk averse when the probability is large, and risk seeking when the probability is small, and vice-versa for the monetary loss domain.

Risk preferences for monetary goods have been elicited with various methods and populations in real and hypothetical scenarios. A majority of studies have found a risk averse behaviour in monetary gain domain; the pattern of risk attitudes stated in prospect theory has also been extensively tested, yet the results are mixed (Harbaugh et al., 2002; Laury and Holt, 2008; Harbaugh et al. , 2010; Barberis, 2013a; Charness et al., 2013). Additionally, studies on risk attitudes in different contexts have reported results that support a context-dependent risk preference. Risk preferences have been found to differ across various aspects of life, for instance, recreational, health and safety, ethical and social aspects (Bleichrodt and Pinto, 2000; Lusk and Coble, 2005; Blais and Weber, 2006; Isik, 2006; Dohmen et al., 2011; Hansson and Lagerkvist, 2012; Reynaud and Couture, 2012; Riddel, 2012). Therefore, a simple assumption of equal risk preference for the monetary and the non-monetary goods may lead to biased results, with potentially little policy relevance.

Probability-specific risk attitudes, a feature that has been found in prospect theory and tested for monetary goods (Harbaugh et al., 2002; Harbaugh et al., 2010; Scholten and Read, 2014), has rarely been investigated for non-monetary goods. A probability-specific risk attitude indicates that the effects of risk on environmental preferences differ depending on the magnitude of the stated probability, as respondents allocate subjective decision weights on these probabilities. This is especially true when respondents severely distort the probabilities in events that have low probabilities but high consequences (Shaw and Woodward, 2008). Thus, for researchers using SP method, understanding the probability-specific heterogeneity in risk attitudes can help to obtain more accurate preference or WTP estimates for a given policy scenario where a small or a large probability of achieving an environmental outcome is presented.

In the SP literature, hypothetical scenarios are often assumed to be certain (Roberts et al., 2008). But increasingly, risk or uncertainty [45] is integrated into hypothetical experimental scenarios in studies using CVM (Johansson 1989; Macmillan et al. 1996; Isik 2006; Koundouri et al. 2014) or DCE (Roberts et al. 2008; Wielgus et al., 2009; Glenk and Colombo, 2011, 2013; Torres et al., 2017; Bojusa et al., 2018). Given the limited scientific knowledge about various aspects of the natural environment, accounting for risk is considered not only as enhancing the credibility of the hypothetical scenario, making the scenario more realistic from the view of respondents (Wielgus et al., 2009), but also as increasing the external validity of SP studies from a policy perspective (Rolfe and Windle, 2015).

In CVM studies, Johansson (1989) and Macmillan et al. (1996) investigate the effects of risk on WTP by using split samples. Environmental improvements are described as certain in one treatment and stated as probable changes in another treatment, yet the expected values of the environmental outcomes in two treatments are set to be equal. These studies find smaller WTP estimates in the risky treatment than the riskless treatment, implying a risk averse preference, whereas Koundouri et al. (2014) find no WTP difference between these two treatments. Most DCEs incorporate information on risk through probabilities (in quantitative or qualitative form) either in the environmental attributes, representing risk around the environmental outcomes, or as an independent attribute in the experimental design. The effects of risk are found to significantly affect individuals' environmental preferences (or WTP), when comparing an uncertain treatment with probabilities of the outcomes specified and a certain treatment without outcome uncertainty (Roberts, et al., 2008; Torres et al., 2017). However, if the probabilities of the environmental outcomes are incorporated in this way, the corresponding expected values of such outcomes for the uncertain treatment will be lower than those in their certain counterpart. Therefore, under the assumption of expected utility theory, the treatment effects (i.e., the effects of risk on utility or WTP) entail two separate components, namely the effect of presenting risk on utility or WTP and the effect of changes in expected environmental outcomes on utility or WTP. Inability to disentangle the two leads to biased estimates of risk effects.

Faccioli et al. (2019) present the only study that disentangles the two components by comparing a certain treatment of outcome delivery of number of specialist bird species to an uncertain treatment of equal expected outcomes. As the expected outcomes in both treatments are equal, the design allows ruling out the possible confounding effect of the changing expected outcomes, and thus allows to estimate the pure effect of presenting risk. However, a limitation in their design is the use of a constant probability throughout, meaning that probability-specific risk effect cannot be examined. The study

[45] I notice that risk implies that the respondent knows the probability of the event/policy, but does not know the actual outcome, while uncertainty implies one does not know the probability of the event/policy and the actual outcome.

furthermore does not present the values of the expected outcomes for the uncertain treatment explicitly, and respondents are assumed to be able to calculate these by themselves. However, it has been shown that mathematical skills and knowledge of expected values significantly affect consistency of respondents' choices and risk preferences (Dave et al., 2010; Taylor, 2016; Kjær et al., 2018).

Building on Faccioli et al. (2019), I address these issues and investigate the effects of incorporating risk in the context of air quality change in China. In the uncertain treatment, the health outcomes caused by air quality changes are specified as probabilistic, whilst health is described as certain in the certain treatment, and the expected health outcomes in both treatments are equalized. Therefore, any utility difference between the two treatments can be interpreted as an effect of presenting risk. A wide range of probabilities is used, with a small and a large chance of occurrence to describe the degree of risk, which enables the estimation of probability-specific risk effects and a link with the fourfold pattern of risk attitudes from prospect theory. Additionally, expected outcomes for the uncertain treatment are explicitly presented as additional information alongside the probabilities and outcomes, ensuring that the information of risk is appropriately conveyed to respondents, whilst any bias due to inability of accurately calculating expected outcomes is minimized.

In contrast with Faccioli et al. (2019), the results in this study suggest that risky choice framing [46] has little effect on individuals' environmental preferences. For the attribute of interest, no significant mean differences are observed in respondents' utilities between the uncertain treatment and the certain treatment in both environmental improvement and deterioration scenarios. However, the spread of the health attribute for the uncertain treatment is found to be smaller than that in the certain treatment.

The remainder of the chapter is structured as follows. Section 4.2 introduces relevant literature. Section 4.3 presents the experimental design and details of the survey. Section 4.4 explains the random utility maximization framework and presents hypotheses to be tested. Section 4.5 presents the descriptive statistics of the two samples followed by hypotheses testing results. In Section 4.6, the implications of the results and limitations are discussed. Section 4.7 provides the conclusion of this study.

4.2 Literature Review

4.2.1 Risk preference for monetary and non-monetary goods

[46] Following the typology of the framing effect in Levin et al. (1998), "risky choice framing" is used as the terminology for the treatment effect of presenting risk in this chapter, as the treatment effect is investigated by comparing the preference estimates in the risky choice scenarios with those in the riskless scenarios.

Risk preference has been studied for decades both in laboratory and field experiments under the assumption of expected utility theory (Gneezy and Potters 1997; Eckel and Grossman, 2002; Tanaka et al., 2010), with people in general being found to be risk averse for monetary gains. Gneezy and Potters (1997) and Eckel and Grossman (2002) have developed two of the earliest risk preference elicitation methods that have been frequently used in experimental economics, due to their simple experimental process. However, both methods are criticized for their inability to obtain a full range of risk attitudes and to distinguish between risk-seeking and risk-neutral preferences or between different classifications of risk-seeking behaviour (Charness et al., 2013). The drawbacks of these methods are overcome by the multiple price lists method, in which a more systematic estimation of the degree of curvature of utility function is conducted, covering all ranges of risk behaviours (Holt and Laury, 2002). Multiple price lists method (and its variations) has also been frequently applied in both laboratory (Andersen et al., 2006; Anderson et al., 2007; Drichoutis and Lusk, 2016) and field experiments (Meier and Charles, 2007; Harrison et al., 2009; Tanaka et al., 2010; Charness and Viceisza, 2016), although some studies criticize this method for its complexity for participants and its inability to obtain consistent estimates (Jacobson and Petrie, 2009; Dave et al., 2010; Charness and Viceisza, 2012).

On the other hand, prospect theory states that risk preferences are domain-dependent (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Respondents are risk averse when the gamble involves monetary gains (from a reference point) and risk seeking when choices are made in the loss domain (see Barberis, 2013a, 2013b for detailed literature review on the applications of the prospect theory). Another important finding from prospect theory is that respondents tend to put subjective decision weights on the probabilities of the outcomes, which affects elicited risk preferences. After the weighting function is accommodated, results suggest a probability-specific risk preference, which is also called a fourfold pattern of risk attitudes. It shows that for small probabilities, respondents are risk seeking in the gain and risk averse in the loss domains, but they are risk averse in the gain and risk seeking in the loss domains when probabilities are large. The fourfold pattern of risk attitudes has been tested in laboratory experiments using hypothetical and real stakes (Harless and Camerer, 1994; Laury and Holt, 2008), and with choice-based elicitation and price elicitation procedures (Harbaugh et al., 2002; Harbaugh et al., 2010).[47] Some studies claim that people's experience tend to affect their decision-making, causing the fourfold pattern less pronounced (Kusev et al., 2009) or even vanished (Hertwig et al., 2004).

[47] Another strand of studies finds that the size of the stake has an impact on risk preference, and this effect also follows a four-fold pattern, theoretically proposed by Markowitz (1952). Fehr-Duda et al. (2010) find that the fourfold pattern regarding stake size is driven (or partly driven) by probability weighting. Some studies claim that the fourfold pattern from Markowitz (1952) can be accommodated with the fourfold pattern from prospect theory under additional assumptions about the utility function (Scholten and Read, 2014; Bouchouicha and Vieider, 2017).

Although risk preference has already been extensively explored for monetary goods, the issue receives less attention in a non-monetary context. In contrast to the beliefs of most economists that individuals' risk preferences are stable across various circumstances, some studies have found that people's risk attitudes are context-dependent (Lusk and Coble, 2005; Blais and Weber, 2006; Isik, 2006; Dohmen et al., 2011; Hansson and Lagerkvist, 2012). Some of the earliest evidence come from Blais and Weber (2006), who elicited the perceived risk preferences of respondents in a variety of contexts, including recreational, health and safety, ethical, social and financial decision making, using context-specific risk-taking scale questions. They found that the variability of within-individual context-specific risk preferences was much larger than the that of between-individual risk preferences, substantiating the significance of variation in risk preferences across different aspects of life for a given individual. Reynaud and Couture (2012) used two common elicitation methods in economics (i.e., the Eckel and Grossman (2002)'s method and multiple price lists method) to estimate risk preference for monetary goods in the lab, and the estimates were compared with risk attitudes for non-monetary goods. Their results suggested that the monetary risk preferences were correlated with risk-taking behaviours in recreational dimensions, but not in other contexts. Two studies used the multiple price lists format to elicit risk attitudes and the degree of probability weighting in environmental decision making; the results were then compared with those for monetary goods (Riddel, 2012; Bartczak et al., 2015). Bartczak (2015) found that respondents' risk preferences were the same in both the financial and environmental dimensions, whilst findings from Riddel (2012) supported different risk preferences between these two domains. As for the weighting function, both studies showed that respondents were more likely to over-weight low probabilities for environmental outcomes, which supported prospect theory rather than expected utility theory. Age was found to play a role in an individuals' risk preferences and probability weighting.

4.2.2 Estimating the effects of risk on preference using stated preference methods

In SP literature, some studies have investigated the effects of monetary risk preference on individuals' environmental preferences (Bartczak, Mariel, et al. 2016; Bartczak, Chilton, et al. 2017). The individual-level risk preferences are elicited using the multiple price lists method and are interacted with taste parameters elicited from DCEs. Results suggest that individual's financial risk attitudes significantly affect their environmental choices. However, given the previous research findings of context-specific risk preferences, risk preferences for monetary goods may provide little implication as to how people make environmental decisions under risk.

Several recent DCE studies have incorporated and presented risk as a probability describing the occurrence of the policy outcomes (Roberts et al. 2008; Wielgus et al., 2009; Rigby et al., 2010; Glenk and Colombo, 2011, 2013; Akitar et al., 2012; Rolfe and Windle, 2015; Torres et al., 2017; Bojusa et al., 2018). Using a split-sample design, Roberts et al. (2008) and Torres et al. (2017) compared a certain treatment with an uncertain treatment where outcome was presented as probability. The effects of introducing risk were found to be significant, implying that respondents considered risk in environmental decision-making, yet the results contrasted with the findings from Glenk and Colombo (2011) in which WTP difference between certain and uncertain treatments was found to be insignificant. A key drawback of these designs is that when making treatment comparisons, the corresponding expected values of the outcomes for the uncertain treatment are lower than their certain counterparts. Therefore, the obtained treatment effects not only include the effect of presenting risk, but also include the effect of changes in expected environmental outcomes under the assumption of expected utility theory. This suggests that the estimated treatment effect is biased.

A few CVM studies have investigated the effects of risk on WTP using a split-sample design where environmental outcomes in one treatment are described as certain, and as uncertain in another treatment (Johansson 1989; Macmillan et al. 1996; Koundouri et al. 2014). As the expected policy outcomes in two treatments are designed to be equal, the estimated risk effects represent the pure effect of introducing risk. Results from Johansson (1989) and Macmillan et al. (1996) suggest that WTPs for the uncertain treatment are smaller than those in the certain treatment, implying a risk aversion behaviour, yet no WTP difference is found in Koundouri et al. (2014).

Using a similar method, Faccioli et al. (2019) investigated the effects of risky choice framing using a DCE, and the investigation was extended to both environmental gains and losses. The results showed that given the same expected outcomes, respondents obtained more utility for environmental improvements in the uncertain treatment than the certain treatment, implying risk seeking behaviour, and obtained less disutility in the certain treatment than the uncertain treatment, implying risk averse behaviour; yet the significance of these effects were not justified. One of the limitations in their design is that only one probability is embedded to represent uncertainty, but the fourfold pattern of risk attitudes states that the effects of risk could differ according to the magnitude of the probabilities. Another limitation is that they do not explicitly show the expected outcomes and assume that respondents have been able to calculate these by themselves. However, some studies have found that mathematical skills and the knowledge of expected values significantly affect choice consistency and risk preferences (Dave et al., 2010; Taylor, 2016). Dave et al. (2010) used 31 real-life problem-solving questions to test respondents' numeracy skills and related the scores with choice consistency under risky choice scenarios. They found that low maths scores were correlated with high inconsistency in decision making. In another experimental study, Taylor (2016) found a relationship between numeracy abilities and risk preferences, and showed that the knowledge of expected values also played a role in risk preferences. The effect of numeracy skills on risk perception was also confirmed in a DCE study on estimating preferences for traffic mortality risk reduction (Kjær et al., 2018). These studies stress the importance of providing additional assistance to respondents whose mathematical abilities are inadequate.

In summary, risk preferences for monetary goods have been studied extensively both in the laboratory and field experiments, and various studies have confirmed the context-dependent nature of risk preferences, implying that people's risk attitudes towards monetary goods and environmental goods may be different. In DCE studies that aim to investigate the effects of introducing risk on WTP/preference estimates, except Faccioli et al. (2019), few studies disentangle the effect of risky choice framing from the effect of the changes in corresponding expected outcomes. Faccioli et al. (2019) only include one probability and does not explicitly show the information of expected outcomes in their design. Therefore, they cannot investigate a probability-specific risky choice framing (i.e., whether the effect of risky choice framing differs in probabilities) and could obtain biased estimates if a large amount of respondents is not able to calculate expected outcomes. These two drawbacks are overcome in the design of this chapter.

4.3 Data source and experimental design

The survey was conducted in Beijing where heavy air pollution occurs. A gain-loss design is applied to reflect the future policy dilemma that a trade-off between air quality improvement and economic development has to be considered. This chapter uses three attributes to represent the effects of air pollution on individuals' wellbeing: health, visibility and cost.

The health attribute is represented by hospital admissions due to air pollution. The health outcome is specified as riskless in a certain treatment, and as risky in an uncertain treatment. In the uncertain treatment, a 20% and a 90% probabilities are used to represent the chance of the occurrence of stated health outcomes.[48] The design of the probabilistic health outcomes is to reflect the difficulty in accurately predicting the air pollution effects. The expected values of the health outcomes for the certain treatment are designed to be equal to those for the uncertain treatment.

The number of "bad visibility" days each month is used to describe the visibility attribute, and the corresponding policy cost is framed as changes in household electricity, gas and central heating bills, which the majority of the people in Beijing need to pay. The final attribute levels for the certain and

[48] Different from the risky design in Chapter 3, in this chapter, the information of probabilities and the corresponding health outcomes are placed in the same attribute.

uncertain treatments are presented in Tables 4.1a and 4.1b. Examples of the choice cards that were presented to respondents for both treatments are given in Figure 4.1a and 4.1b.

Table 4.1a Attributes and levels for the certain treatment

Attributes	**Environmental Deterioration**			**Current Situation** [a]	**Environmental Improvement**		
Health effect (1,000 hospital admissions/year)	150	145	140	130	120	115	110
Visibility effect (bad visibility days/month)	/	12	10	8	6	4	/
Change in electricity, gas and heating bill (RMB/month)	500 RMB [b] decrease	300 RMB decrease	100 RMB decrease	No change in bill	100 RMB increase	200 RMB increase	500 RMB increase

Note: (a) Current Situation is the attribute level under current air pollution implementation. (b) According to China National Bureau of Statistics, the deposable income per capita in 2017 in China is 25,974 RMB (i.e., £2,966, according to the exchange rate on 06/09/2019).

Table 4.1b Attributes and levels for the uncertain treatment

Attributes	**Environmental Deterioration**			**Current Situation**[a]	**Environmental Improvement**		
Probabilities and the corresponding health outcomes (1,000 hospital admissions/year) [b]	20%	90%		100%	20%	90%	
	180	*141*			*30*	*108*	
	205	*147*		*130*	*55*	*113*	
	230	*152*			*80*	*119*	
Visibility effect (bad visibility days/month)		12	10	8	6	4	
Change in electricity, gas, heating bill (RMB/month)	500 RMB [c] decrease	300 RMB decrease	100 RMB decrease	No change in bill	100 RMB increase	200 RMB increase	500 RMB increase

Note: (a) Current Situation is the level of attributes under current air pollution implementation. (b) In total, there are twelve levels for the health attribute in alternative scenarios; half of the stated health outcomes can be achieved with 20% chance and the other half achieved with 90% chance. (c) According to China National Bureau of Statistics, the deposable income per capita in 2017 in China is 25,974 RMB (i.e., £2,966, according to the exchange rate on 06/09/2019).

	Policy A	**Policy B**	**Current policies**
Health (hospital admissions/year)	**145** thousand per year (**15** thousand **more** or **11%** more)	**120** thousand per year (**10** thousand less or **7.5%** less)	**130** thousand per year (no change)
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)	**4** days of bad visibility per month (**4** days less)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	**100** RMB decrease/month （**1,200** RMB decrease/year）	**100** RMB increase/month （**1200** RMB increase/year）	No change in bill

Figure 4.1a An example of a choice card for the certain treatment

	Policy A	**Policy B**	**Current policies**
Health (hospital admissions/year)	**90%** chance to have **119** thousand hospital admissions per year **(11** thousand or 8.3% less) 10% chance of no change average hospital admissions =120 thousand per year	**90%** chance to have **113** thousand hospital admissions per year **(17** thousand or **12.5%** less) 10% chance of no change average hospital admissions =115 thousand per year	**130** thousand hospital admissions per year (no change)
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)	**12** days of bad visibility per month (**4** days more)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	**500** RMB per month bill increase (**6000** RMB per year bill increase)	**200** RMB per month bill increase (**2400** RMB per year bill increase)	No change in bill

Figure 4.1b An example of a choice card for the uncertain treatment

Two D-efficient fractional-factorial designs were generated and applied to the riskless and risky treatments, and two blocks of ten choice sets were constructed for each treatment. Order effects were minimized and unrealistic policy scenarios were avoided, in the same way as stated in Chapter 2.

4.4 Modelling framework

4.4.1 Random utility model

DCE data is analysed within a random utility maximization framework (McFadden, 1974), where respondents are assumed to maximise their utility when choosing alternatives:

$$U_{ni} = \beta X_{ni} + \varepsilon_{ni} \tag{4.1}$$

In Equation 4.1, U_{ni} is the utility of individual n choosing alternative i, X_{ni} is the attribute vector representing the deterministic part of the utility function, while ε_{ni} (i.e., error term) represents a stochastic component following a Gumbel distribution.

I apply an asymmetric gain-loss specification for both the certain and uncertain treatments under expected utility assumption, where the health attribute is separated according to whether expected health outcomes are stated as improvements or deteriorations relative to a reference point (i.e., the current health level):

$$U_{ni} = \alpha_n(\beta_{ASC} ASC_{SQ,i} + \beta_H^{imp} H_{ni}^{imp} + \beta_H^{det} H_{ni}^{det} + \beta_V V_{ni} + \beta_C C_{ni}) + \varepsilon_{ni} \tag{4.2}$$

In Equation 4.2, $ASC_{SQ,i}$ represents the alternative specific constant for the status quo alternative. H^{imp}= max(H_{SQ}–H_{ni}, 0) indicates an improvement in the health attribute in alternative i relative to the current health outcome, and H^{det} = max($H_{ni} - H_{SQ}$, 0) indicates a deterioration in the health attribute. The scale parameter α_n, which has an inverse relationship with the variance of the error term, is parameterized to capture the scale heterogeneity between the certain and the uncertain treatment (Swait and Louviere, 1993). $\alpha_n = \exp(\lambda \cdot T_n)$, where T_n is a dummy variable taking the value 1 if an individual belongs to the certain treatment and equalling to 0 if a respondent belongs to the uncertain treatment; λ is an estimable parameter for the scale difference. Visibility and cost is assumed to be certain and linear in utility.

4.4.2 Hypotheses

To test whether there are treatment-specific (i.e., risky choice framing) effects in the gain and loss domains, I estimate models with the following utility specification:

$$U_{ni} = \alpha_n(\beta_{ASC}ASC_{SQ,i} + \beta_{H(uct)}^{imp}H_{ni}^{imp}(1-T_n) + \beta_{H(ct)}^{imp}H_{ni}^{imp} \cdot T_n + \beta_{H(uct)}^{det}H_{ni}^{det}(1-T_n) + \beta_{H(ct)}^{det}H_{ni}^{det} \cdot T_n + \beta_V V_{ni} + \beta_C C_{ni}) + \varepsilon_{ni} \quad (4.3)$$

where $\beta_{H(uct)}^{imp}$ ($\beta_{H(ct)}^{imp}$) measures the expected health effects of the uncertain (certain) treatment in the gain domain and $\beta_{H(uct)}^{det}$ ($\beta_{H(ct)}^{det}$) measures the expected health effects of the uncertain (certain) treatment in the loss domain.

Hypothesis 1a (H1a): Respondents obtain lower utility gains in the uncertain treatment than the certain treatment when the expected health outcomes are described as improvements.

Hypothesis 1b (H1b): Respondents obtain lower utility losses in the uncertain treatment than the certain treatment when the expected health outcomes are described as deteriorations.

The null hypotheses of H1a and H1b are:
H1a: $\beta_{H(uct)}^{imp} \geq \beta_{H(ct)}^{imp}$
H1b: $\beta_{H(uct)}^{det} \leq \beta_{H(ct)}^{det}$

The alternative hypotheses are:
H1a: $\beta_{H(uct)}^{imp} < \beta_{H(ct)}^{imp}$
H1b: $\beta_{H(uct)}^{det} > \beta_{H(ct)}^{det}$

It is expected that respondents experience higher utility gain (loss) in the certain treatment from a given health improvement (deterioration) than the uncertain treatment, which implies risk averse (seeking) behaviour in the environmental gain (loss) domain.

In the previous tests, different probabilities are assumed to not affect individuals' environmental preferences, as long as the final expected outcomes are the same. However, to account for the probability-specific effects, the health variable in each domain is split into two, with one representing a small (i.e., 20%) probability and the other representing a large (i.e., 90%) probability. This is given by the equation below:

$$U_{ni} = \alpha_n(\beta_{ASC}ASC_{SQ,i} + \beta_{H(20)}^{imp}H_{ni}^{imp(20)}(1-T_n) + \beta_{H(90)}^{imp}H_{ni}^{imp(90)}(1-T_n) + \beta_{H(ct)}^{imp}H_{ni}^{imp} \cdot T_n + \beta_{H(20)}^{det}H_{ni}^{\mathrm{det}(20)}(1-T_n) + \beta_{H(90)}^{det}H_{ni}^{\mathrm{det}(90)}(1-T_n) + \beta_{H(ct)}^{det}H_{ni}^{det} \cdot T_n + \beta_V V_{ni} + \beta_C C_{ni}) + \varepsilon_{ni} \quad (4.4)$$

where $\beta_{H(20)}^{imp}$ ($\beta_{H(20)}^{det}$) and $\beta_{H(90)}^{imp}$ ($\beta_{H(90)}^{det}$) are linear variables measuring the effects of health on utility in the gain (loss) domain with a 20% and a 90% probability of delivering the associated health outcomes, respectively.

Hypothesis 2a (H2a): In the gain domain, where air pollution-related expected health outcomes are described as improvements, respondents obtain higher utility in the uncertain treatment than the certain treatment, when the probability of the health outcome is small.

Hypothesis 2b (H2b): In the gain domain, respondents obtain lower utility in the uncertain treatment than the certain treatment, when the probability of the health outcome is large.

Hypothesis 2c (H2c): In the loss domain, where air pollution-related health is described as deteriorations, respondents obtain higher utility loss in the uncertain treatment than the certain treatment, when the probability of the health outcome is small.

Hypothesis 2d (H2d): In the loss domain, respondents obtain lower utility loss in the uncertain treatment than the certain treatment, when the probability of the health outcome is large.

The null hypotheses of the above four hypotheses are:
H2a: $\beta_{H(20)}^{imp} \leq \beta_{H(ct)}^{imp}$
H2b: $\beta_{H(90)}^{imp} \geq \beta_{H(ct)}^{imp}$
H2c: $\beta_{H(20)}^{det} \geq \beta_{H(ct)}^{det}$
H2d: $\beta_{H(90)}^{det} \leq \beta_{H(ct)}^{det}$

The alternative hypotheses are:
H2a: $\beta_{H(20)}^{imp} > \beta_{H(ct)}^{imp}$
H2b: $\beta_{H(90)}^{imp} < \beta_{H(ct)}^{imp}$
H2c: $\beta_{H(20)}^{det} < \beta_{H(ct)}^{det}$
H2d: $\beta_{H(90)}^{det} > \beta_{H(ct)}^{det}$

Preference heterogeneity can be modelled through mixed logit models (Hensher and Greene, 2013), where attribute parameters are decomposed into a fixed and a random component, with the latter part following a pre-assumed distribution. Under a panel data structure, health, visibility and the alternative specific constant parameters are assumed to be random and following normal distributions, while the cost attribute is assumed to be fixed. To reflect the possibility that preferences for the 20% and 90% choice situations can be correlated (i.e., an individual who has a high sensitivity to the health outcomes with 20% probability may also have a high sensitivity to the health outcomes with 90% probability), the probability-specific model (Equation 4.4) accounts for correlation between the 20% and 90% probability random parameters. Models are estimated using the Apollo package (Hess and Palma, 2019) based on 500 MLHS (Modified Latin Hypercube Sampling) draws for random parameters.

The above hypotheses are based on the mean parameters, and the mean differences are tested using the Wald test. In addition, individual-level conditional means of the random health parameters are obtained using simulation with 500 draws (see Section 2.4.5 for the detailed modelling process), and Mann–Whitney U test (Mann and Whitney, 1947) is applied to test the distributional differences between the health parameter of the certain treatment and the health parameter of the uncertain treatment. This test has been used in some DCE studies to examine distributional differences of conditional estimates from two groups of data (Aravena et al., 2014; Hagedoorn et al., 2020). For the treatment-specific effects, the null hypothesis is that the distribution of the conditional means of the health parameter of the certain treatment is equal to that of the uncertain treatment for the gain (loss) domain, whilst the alternative hypothesis is that the compared distributions are unequal (i.e., two-sided tests are conducted here). The same applies to distributional tests of the probability-specific effects, where two pair-wise comparisons (i.e., the health parameter of the certain treatment versus the 20% or 90% health parameter of the uncertain treatment) are conducted for each domain.

4.5 Results

4.5.1 Descriptive statistics

The survey was completed by 230 respondents per treatment. Sample descriptive statistics are given in Table 4.2. First, individual characteristics are not significantly different at a 1% level between the certain and uncertain treatments. Second, comparisons of the characteristics between the Beijing general population and the sample in two treatment groups suggest that the sample tends to be more educated and younger. Of those who completed the survey, I exclude respondents with no variation in their DCE answers (i.e., people who constantly chose Policy A or Policy B, and those who chose the status quo option constantly for the belief that citizens do not need to pay for air quality improvement). The final dataset used in modelling analysis includes 226 respondents in the certain sample and 221 in the uncertain sample.

Table 4.2 Summary statistics of respondent characteristics (Chapter 4)

Variables	**Certain treatment**	**Uncertain treatment**	**General population** [c]
Age			
18-25 years	4.8%	4.4%	21%
25-35 years	46.5 %	44.4%	23%
35-45 years	39.6 %	38.7%	19%
45-55 years	7.8 %	10.9%	18%
>55 years	1.3 %	1.7%	20%
Gender (male %)	48.2 %	51.3%	51.2%
Highest level of education completed			
High school or lower	0.4 %	0.9%	67%
Undergraduate	94.4 %	93.9%	29%
Postgraduate or higher	5.7 %	5.2%	4%
Annual gross income (RMB)			
80,000 or less	8.3%	10.9%	
80,000-200,000	66.5%	63.9%	
200,000-300,000	19.6%	21.7%	
300,000 or higher	5.7%	3.5%	
Income (mean) [a]	168,690	164,680	113,073
Responsible for bill [b]	92.8%	93.9%	
Sample size	230	230	

Note: (a) The mean of the income for the sample is represented by weighted sum of the means of each income category; (b) Responsible for bill is the self- reported responsibility for the household bill (Yes/No). (c) Age and education data for the general population are from the 2010 Population Census of China, and gender and income data are from the Beijing Statistical Yearbook 2017.

4.5.2 Estimation results and hypotheses testing

The results of the mixed logit models are presented in Table 4.3. In the treatment-specific model (model 1), the significantly negative coefficient of the alternative specific constant implies that respondents are more likely to choose the proposed new policies than the status quo option (i.e., current policies). The significant and positive (negative) signs of the H^{imp} (H^{det}) variables in both treatments indicate that respondents obtain utility (disutility) when health is improved (deteriorated). The sign of the visibility variable suggests a significantly negative correlation between the number of bad visibility days and respondents' utility. The significant and negative sign of the cost attribute indicates that respondents take into account the bill changes when making trade-offs. Additionally, the sign of the estimable parameter associated with the scale of the uncertain treatment is positive, albeit not significant at a 5% level, implying that no significant difference has been observed in terms of choice randomness between the two treatments. One would expect the variance to be different when respondents make less random choices in the uncertain treatment due to the increased credibility of the experimental scenario (Wielgus, 2009), whilst it could also be that they make more random choices in the uncertain treatment than the certain treatment due to higher cognitive burden in processing the information on risk.

Table 4.3 Mixed logit model results for preference changes for air pollution attributes

	Treatment-specific model (model 1)		**Probability-specific model (model 2)**	
Variables [a]	Coefficient	S.E.	Coefficient	S.E.
Cost	-0.0003***	(0.0001)	-0.0003***	(0.0001)
λ (Scale parameter)	0.111	(0.117)	0.195*	(0.118)
Random parameters (mean)				
ASC SQ	-0.979***	(0.133)	-0.915***	(0.129)
H^{imp} (Certain)	0.522***	(0.100)	0.555***	(0.101)
H^{imp} (Uncertain)	0.595***	(0.117)		
$H^{imp(20)}$ (Uncertain)			0.670***	(0.132)
$H^{imp(90)}$ (Uncertain)			0.482***	(0.101)
H^{det} (Certain)	-0.921***	(0.146)	-0.872***	(0.139)
H^{det} (Uncertain)	-0.658***	(0.144)		
$H^{det(20)}$ (Uncertain)			-0.737***	(0.152)
$H^{det\,(90)}$ (Uncertain)			-0.569***	(0.133)
Visibility	-0.097***	(0.014)	-0.093***	(0.014)
Standard deviations of the random parameters				
ASC SQ	1.586***	(0.159)	1.547***	(0.151)
H^{imp} (Certain)	1.008***	(0.110)	1.086***	(0.117)
H^{imp} (Uncertain)	0.490***	(0.139)		
$H^{imp(20)}$ (Uncertain)			0.754***	(0.155)
$H^{imp(90)}$ (Uncertain)			0.191 [b]	(0.164)
$H^{imp(20\&90)}$ (Uncertain)			0.259**	(0.118)
H^{det} (Certain)	1.613***	(0.155)	1.581***	(0.150)
H^{det} (Uncertain)	1.375***	(0.193)		
$H^{det(20)}$ (Uncertain)			1.384***	(0.204)
$H^{det\,(90)}$ (Uncertain)			0.425*** [b]	(0.118)
$H^{det(20\&90)}$ (Uncertain)			1.158***	(0.181)
Visibility	0.150***	(0.018)	0.149***	(0.018)

Table 4.3 Continued

Model statistics		
AIC	7947	7929
BIC	8037	8058
Log-likelihood	-3960	-3945
n(observations)	4,470	4,470

Note: (a) ASC SQ is the alternative specific constant for the "current policies" (status quo) option; $\mathrm{H^{imp}}$ (Certain) ($\mathrm{H^{det}}$ (Certain)) is the health attribute in the gain (loss) domain for the certain treatment, whilst $\mathrm{H^{imp}}$ (Uncertain) ($\mathrm{H^{det}}$ (Uncertain)) is the health attribute in the gain (loss) domain for the uncertain treatment; $\mathrm{H^{imp(20)}}$ (Uncertain) and $\mathrm{H^{det(20)}}$ (Uncertain) are the health attributes with a 20% probability in the gain and loss domains respectively, whilst $\mathrm{H^{imp(90)}}$ (Uncertain) and $\mathrm{H^{det(90)}}$ (Uncertain) are the health attributes with a 90% probability in the gain and loss domains for the uncertain treatment; $\mathrm{H^{imp(20\&90)}}$ (Uncertain) and $\mathrm{H^{det(20\&90)}}$ (Uncertain) are the standard deviation parameters capturing the correlation between the 20% and 90% probability parameters in the gain and loss domains respectively. Visibility is the visibility attribute; Cost is the cost attribute. (b) The standard deviation of $\mathrm{H^{imp(90)}}$ (Uncertain) after accounting for correlation is 0.321 with its standard error being 0.094. The standard deviation of $\mathrm{H^{det(90)}}$ (Uncertain) after accounting for correlation is 1.233 with its standard error being 0.461. These standard deviation parameters are calculated using the standard deviation estimates according to the formula $\sqrt{(\mathrm{H^{(90)}(Uncertain)})^2 + (\mathrm{H^{(20\&90)}}\ (\mathrm{Uncertain}))^2}$, and the standard errors are calculated using the Delta method. (c) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

The model fit of the treatment-specific utility specification (model 1) is not significantly better than that of the combined specification (model 3, Table C.1 in Appendix C.1), based on a likelihood ratio test (p-value>0.1), which is inconsistent with Faccioli et al. (2019). This result is a first indication that when expected outcomes in two treatments are equal, presenting outcomes as certain or uncertain in choice scenarios (i.e. risky choice framing) has little effect on respondents' preferences in the context of air pollution, even after the scale difference between the two treatments are accounted for.

For Hypothesis 1, the mean effect of the health improvement for the uncertain treatment (i.e., $\mathrm{H}^{\mathrm{imp}}$ (Uncertain)) is slightly larger than that for the certain treatment (i.e., $\mathrm{H}^{\mathrm{imp}}$ (Certain)), but not statistically different (one-sided test; p-value>0.1). In the loss domain, the absolute value of mean health deterioration for the uncertain treatment (i.e., $\mathrm{H}^{\mathrm{det}}$ (Uncertain)) is smaller than that for the certain treatment (i.e., $\mathrm{H}^{\mathrm{det}}$ (Certain)), but again this difference is statistically insignificant (one-sided test; p-value >0.1). Overall, the null hypotheses of both H1a and H1b cannot be rejected.

Turning to Hypothesis 2, the results from Model 2 in Table 4.3 show that in the gain domain, respondents obtain higher (lower) utility in the uncertain treatment than the certain treatment when a small (large) probability is presented, which is consistent with the four-fold risk pattern. In the loss domain, respondents experience lower disutility in both small and large probability scenarios in the uncertain treatment than the certain treatment. Despite these small differences in absolute levels, the null hypotheses of H2a, H2b, H2c and H2d cannot be rejected at a 5% significance level (one-sided tests; p-values>0.1 for H2a, H2b and H2c, and >0.05 for H2d).

To evaluate the differences in random parameters, both means and standard deviations, i.e. the entire distributions, have to be considered. This is especially concerning, as the standard deviations of the health attribute parameters in both models are larger than their corresponding means. Therefore, I investigate the distributional differences of the conditional means of health parameters between the certain and uncertain treatments. For the first two pair-wise comparisons, where the health parameter for the certain treatment is compared against that for the uncertain treatment in both domains, results suggest that in the gain domain, the spread of the health attribute for the certain treatment is larger than that for the uncertain treatment, yet this effect is less salient in the loss domain (see Figure 4.2a and 4.2b). A similar pattern is found for the probability-specific model, where the health parameters are split into two according to the magnitude of risk (see Figure 4.3a and 4.3b). Results from the Mann–Whitney U tests suggest that the null hypothesis of equal distribution can be rejected at a 1% significance level for all pair-wise comparisons.

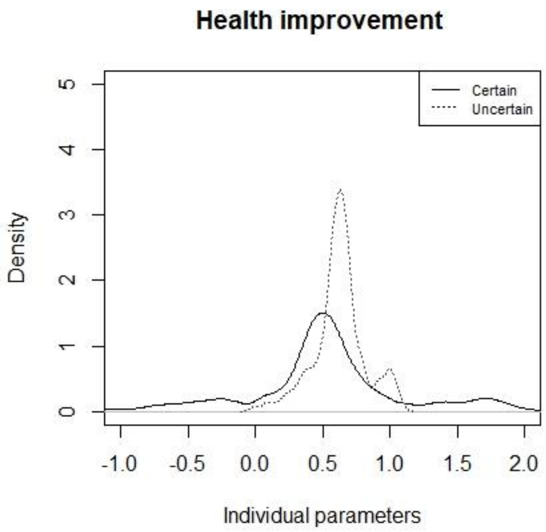


Figure 4.2a The distributions of the conditional means of the health improvement parameters (obtained from the treatment-specific model)

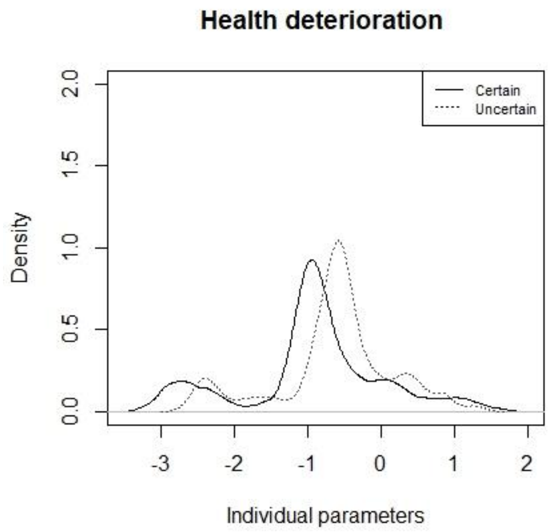


Figure 4.2b The distributions of the conditional means of the health deterioration parameters (obtained from the treatment-specific model)

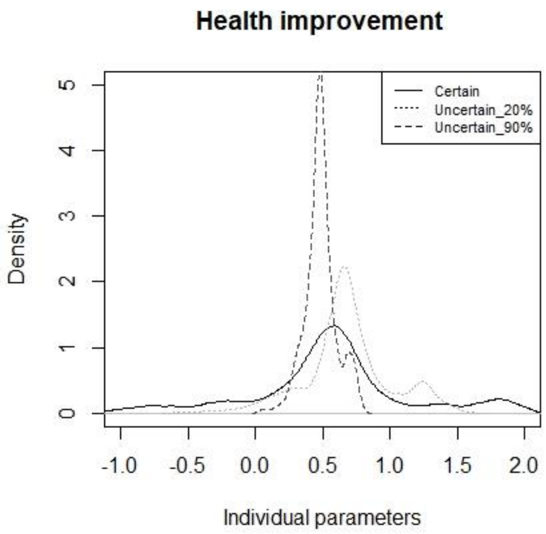


Figure 4.3a The distributions of the conditional means of the health improvement parameters (obtained from the probability-specific model)

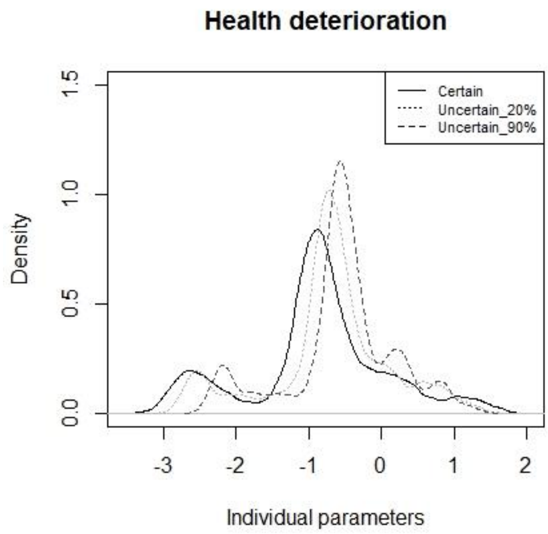


Figure 4.3b The distributions of the conditional means of the health deterioration parameters (obtained from the probability-specific model)

In mixed logit model, large standard deviation implies large preference heterogeneity across individuals. Under the assumption that respondents in both treatments have equal tastes, I analyse such heterogeneous preferences by adding interaction terms of socio-economic variables with the health variables for the uncertain treatment (see Table C.2 in Appendix C.2). This provides us with insight into which social groups are more sensitive towards the effects of risky choice framing. The findings suggest that women obtain less utility than men in the uncertain treatment in the gain domain, which is consistent with findings for monetary goods that woman are more risk averse than men (Lejuez et al., 2002; Weber et al., 2002; Holt and Laury, 2002; Eckel and Grossman, 2002, 2008). Interestingly, respondents claiming not to want air quality to deteriorate obtain more disutility in the uncertain treatment when health is specified as a deterioration, implying higher risk aversion.

As robustness checks, I tested the treatment-specific model using a higher number of draws (1000 MLHS draws) and different distributional assumptions (i.e., log-normal, symmetric triangular, Johnson SB distribution and normal distribution with a second-order polynomial (Fosgerau and Mabit, 2013)). Despite convergence issues under some complex distributions (i.e., Johnson SB and normal distribution with a second-order polynomial), results remain qualitatively unchanged compared to the normal distribution. A random regret model is applied to test if regret minimization rather than utility maximization is assumed during the process of environmental decision-making. The speculation comes from the existence of the deterioration scenarios in the experiment. Given the moral choice nature of this DCE (i.e., a trade-off between monetary compensation and air quality improvement), respondents may experience a great amount of regret induced by negative emotions in their decision making. Therefore, results from a random regret model (i.e., u-RRM model (van Cranenburgh et al., 2015)) based on the behavioural assumption of regret minimization are compared with those from the pre-assumed RUM model (both in an MNL form). Results show that the *u* parameter in the u-RRM model is significant, suggesting that the random regret minimization model does not outperform the model based on random utility maximization. Model details are described in Appendix C.3, followed by the results of the u-RRM model, which are presented in Table C.3 in Appendix C.3).

4.6 Discussion

The effects of presenting risk on preferences for environmental goods are poorly understood in the SP literature. This chapter investigates the effects of incorporating risk in policy scenarios for air quality changes using a split-sample design. One of the environmental attributes is specified as probabilistic in the uncertain treatment, whilst it is riskless in the certain treatment, and the expected outcomes of this attribute are set to be equal in the two treatments. Different from previous studies, the expected outcomes for the uncertain treatment are explicitly given, alongside the probabilities and outcomes, in order to minimize the bias due to inability of calculating the expected outcomes.

Contrary to Faccioli et al. (2019), the risky choice framing is found to have little effect on individuals' preferences for air quality changes, even after the scale difference is accounted for. The mean and distributional differences of parameters of interest between the certain and uncertain treatments are compared. For the mean differences, I do not find that respondents' preferences are significantly deviate from risk neutrality in both the gain and the loss domains. The results are different from studies eliciting risk preferences for monetary goods, where risk aversion is commonly found in the gain domain, and either risk seeking or risk aversion is found in the loss domain. The difference suggests that risk preferences are context-specific (Blais and Weber, 2006; Wilson et al., 2011; Hansson and Lagerkvist, 2012; Riddel, 2012). Evidence from the probability-specific model suggest that for the same expected outcomes, presenting small or large probabilities does not significantly affect respondents' utility in both the gain and loss domain. For the distributional differences, in the gain domain, the standard deviation of the health parameter for the certain treatment is larger than that for the uncertain treatment. One possible explanation is that respondents consider choice scenarios to be more realistic when the risk of health outcomes is incorporated in the experiment (Wielgus et al., 2009), which results in less variance in preference estimates. In addition, in results that are not reported in this thesis (available upon request), I find that respondents in the uncertain treatment have spent significantly more time (p-value<0.1) on average on the DCE than those in the certain treatment. Therefore, the lower variance of the health parameter for the uncertain treatment may also be the consequence of the longer time respondents have spent on choice tasks (Bonsall and Lythgoe, 2009; Hess and Stathopoulos, 2013).

This chapter also contributes to the literature of risk communication in SP method. Literature has been focusing on the best format to communicate risk with additional tools presented together with the numerical probability. Some studies show that graphic representation and descriptive words of probability help to convey the information of risk better (see Visschers, et al. (2009) for a review of risk communication literature). In this study, the expected outcomes of the uncertain attribute are explicitly presented as complementary information, rather than leave it to the respondents to calculate. In a post-experiment question, 93.5% respondents claimed that they did not ignore the information of expected outcomes in the health attribute, which shows that this information has been considered in their decision making. In lab experiments, risk preference for monetary goods is usually obtained using a systematic elicitation method through repeated one-dimensional gambles, i.e., respondents only need to consider a binary outcome and its associated probabilities in each gamble. Moreover, participants are usually students who have gone through basic mathematic training. However, respondents in DCE surveys usually need to consider multi-attribute policy scenarios for the environment, which may cause additional cognitive burden. Furthermore, the samples used in DCEs are normally from the general population who may have received less mathematic training on average than students. Providing information of expected values simplifies the comparisons between policy options in a DCE, while information of risk is still conveyed to respondents through probabilities stated in policy scenarios. Different from the results obtained from some DCE studies that incorporate risk in choice scenarios, the risky choice framing does not significantly affect respondents' environmental preferences in this study, implying that people will behave as risk-neutral when full information is provided.[49] For future DCEs that intend to estimate preference for environmental policies with uncertain outcomes, it is encouraged to include the expected outcomes of the environmental goods in DCE scenarios as an assisting tool in decision making, so that the obtained welfare estimates will not be biased by respondents' knowledge of expected values and mathematical skills. In addition, since risk is a complex concept to the general public, using various qualitative methods to facilitate risk communication before and during the experiment is particularly important in DCE studies where risk is incorporated in the hypothetical scenarios. One promising strategy is applying a think-aloud method in questionnaire pre-testing to gain more knowledge about respondents' understanding and decision strategies used in processing the risk attribute (Ryan et al., 2009; Kløjgaard et al., 2012). During a think-aloud procedure, respondents are asked to verbalise whatever comes into their mind as they go through the experiment, and the qualitative findings can be used to inform risk communication strategy in DCE (Vass et al., 2019). Another propitious tool is using interactive training materials rather than pure-words information, which may enhance respondents' ability and motivation to complete a DCE (Veldwijk et al., 2016; Vass et al., 2020). This is especially effective when the experiment involves complex design or the education level of the targeted population is relatively low (Vass et al., 2020). In a recent study, Vass et al. (2020) found that respondents who had been given an animated storyline (i.e., a video that contained animations and narratives aiming to keep respondents engaged in the DCE scenarios) as training material made less random choices and were less likely to ignore attributes in decision making than those who have been given a plain text scenario description.

Some limitations are acknowledged. First, the change of the expected outcomes in the health attribute for the uncertain treatment is small relative to its reference point. Several studies found that the size of stakes in experimental scenarios influences risk preference (Bosch-Domènech and Silvestre, 2006; Post et al., 2008; Scholten and Read, 2014; Fehr-Duda et al., 2010), with more risk aversion (seeking) being found for larger stakes in the gain (loss) domain (Markowitz, 1952). Thus, it is possible that the size of changes in the risky attribute was not large enough to account for the effects of outcome size

[49] It is acknowledged that if the research aim is to investigate the effect of providing the information of expected outcomes, a separate treatment is needed to disentangle the effect of risky framing from the effect of providing the information of expected outcomes. However, this chapter emphasizes the needs to provide expected outcomes together with the risky policy outcomes to assist calculation and understanding under the assumption of expected utility theory. Given that calculating the expected values of the policy outcomes in this experiment is mathematically demanding, the inclusion of the information of expected outcomes should be appropriate. The gap is left for future research who is interested in the sole effect of including the information of expected outcomes.

(in a relative form) on respondents' risk preferences. Future studies should further explore the stakes dimension and its effect on risk. Second, only two probabilities are presented in the experiment; more data points may be needed to capture probability-specific effects. Whilst more levels of probabilities are cautiously recommended for future studies, researchers may need to trade off the ability to estimate probability-specific effects accurately and the cost of additional cognitive burden for respondents. Third, although the design of varying probabilities allows for testing whether the risk effects are sensitive to the magnitude of probability, the number of levels of the health attribute in each treatment is different, which adds complications to the interpretation of the results. Future research may present one probability value in each treatment to eliminate this possible experimental bias. Finally, the calculation and presentation of expected outcomes are based on the expected utility assumptions which may not be optimal if respondents mainly rely on information such as probability or health outcomes alone for decision making rather than considering all information in the health attribute. On the other hand, heuristic decision making could also occur if respondents only look at the expected outcomes and ignore the stochastic nature of the health outcomes. Future research is needed to better understand what information respondents will use to make decisions under risk when they are presented with both the probabilities and expected outcomes.

4.7 Conclusion

The aim of this chapter is to estimate the effects of presenting risk on individuals' preferences for air quality changes using a DCE, where environmental attributes could either improve or deteriorate. A special between-subjects design is applied in which environmental outcomes in one treatment are described as certain and are stated as uncertain in the other treatment. Expected outcomes in both treatments are set to be equal, and the information about expected outcomes are embedded explicitly in the attribute to assist the calculation under the assumption of expected utility theory. Results suggest that respondents are insensitive to the risky choice framing, and this finding does not change according to whether a large or a small probability is presented. This chapter provides additional evidence of context-specific risk preference, suggesting that risk preferences for monetary goods may not be transferable to environmental dimension. This chapter also reiterates the importance of offering effective risk communication in the experiment so that the elicited preference estimates will not be biased by any confusion related to the misunderstanding of the experiment.

Chapter 5

General Discussion and Conclusion

Air pollution annually causes over a million premature deaths in China and a reported 0.7% GDP loss (Gu et al., 2018). Although strict policies have been implemented to combat the pollution issue, China's energy consumption still relies heavily on the coal industry where most air pollution originates. As a total prohibition of the polluting industry would have a negative impact on China's economic growth, from a policy perspective, the central government has to decide whether to sacrifice the growth of economic benefits to reduce air pollution, or to maintain economic growth at the expense of air quality. Moreover, as environmental outcomes are not completely predictable due to inadequate understanding about the effects of interaction between human and nature, the policy outcomes are not certain. Therefore, welfare measure is needed when either more relaxed or more strict policies on air pollution could happen in the future, and how people will react to policy outcomes that are stated as probabilistic, needs to be studied.

5.1 Key findings

Based on the fact that either increased or reduced policy actions could happen in China, and that there will be uncertainty around the achievement of policy outcomes, this thesis aims to elicit individuals' utility/disutility towards air quality changes using DCEs. In the experimental designs, both improvement and deterioration scenarios are presented in the hypothetical policy options, which allows the preference estimates in the gain and the loss domain to be estimated simultaneously.

Chapter 2 tests loss aversion preference for environmental goods and studies the effects of social capital on individuals' environmental preferences and on loss aversion. Results suggest that loss aversion is found in attributes of air quality. Social capital is positively correlated with preferences for environmental improvement and positively related to disutility from environmental deterioration. In a sub-sample where outliers of loss aversion indices are excluded, higher social capital is also found to be correlated with higher loss aversion preference.

Chapter 3 investigates the ways in which respondents incorporate risk in environmental decision making. This chapter contributes to investigate outcome-related risk perceptions for environmental outcomes in both the gain and loss domains together, and to examine differences in decision making between the two domains under a range of popular economic decision making assumptions under risk. Results reveal that direct risk aversion specification, which implies that individuals have direct distaste towards risk per se disregarding the associated environmental outcomes, can best explain respondents' risk behaviour in the context of air pollution.

Chapter 4 takes an alternative perspective and explores the effects of risky choice framing. Air quality outcomes are specified as certain in one sample, and as uncertain but of equal expected outcomes in another sample. The design allows to disentangle the risk effects from other confounding effects under the assumption of expected utility theory. The results suggest that presenting risk in policy scenarios has little effect on respondents' preferences for air quality.

5.2 Further discussion

5.2.1 WTPs for air quality in China

This thesis contributes to preference and welfare estimates for air quality improvement in China using the SP method. In this thesis, the WTP for the health attribute in Chapter 2 is 5,556 RMB/ household/year in the asymmetric specification (this is calculated according to the results in Table 2.10). To make it comparable with individual WTPs from other studies, the household-level WTP is divided by the average household size in the sample (i.e., 2.96). The final individual-level WTP is 1,877 RMB/year, which is several times higher than many CVM and DCE studies in China (see Table 5.1). One possible reason is that people located in more polluted areas (e.g., Beijing) are willing to pay more for better air quality (Sergi et al., 2019). Another reason could be that individual income in Beijing, the capital of China, is relatively higher than that in other study areas, and hence citizens have higher ability-to-pay.

The thesis also finds that in all the three treatments (i.e., Treatment 1 in Chapter 2, Treatment 2 in Chapter 3 and Treatment 3 (i.e., the uncertain treatment) in Chapter 4), the health attribute is always given a greater weight by respondents compared to other attributes (i.e., visibility, cost or risk). This finding is consistent with other DCE studies conducted in China, where air quality preference is estimated (see Table 5.2),[50] implying that the adverse health effect of air pollution is the most important concern. Additionally, I elicit preference for improving visibility in this thesis, which has not been considered in DCE studies conducted in China. Bad visibility may cause traffic jams/accidents, flight cancellation and restricted outdoor activities (Zhuang, 2016). The impact of visibility is non-negligible in this thesis, as the individual-level WTP for a one-day reduction of bad visibility is estimated at 166 RMB/year (Chapter 2), which is more than 10% of citizen's average annual expenditure on daily necessities in Beijing (National Statistical Bureaus of China, 2019). This result emphasizes the welfare loss due to limited visibility in addition to the health effect.

This thesis (Chapter 2) also finds that people experience loss aversion in both health and visibility attributes. A direct message from loss aversion behaviour is that the welfare loss due to air quality deterioration is larger than the welfare gain from same-sized air quality improvement, implying that

[50] This can be found either by comparing the magnitude of the coefficient or the WTP of the health-related air pollution attributes with non-health attributes.

the social costs of air quality deterioration can be higher than the benefits gained from improvement of equal quantity. In a DCE study, Sergi et al. (2019) have also found evidence of loss aversion in avoiding exposure to sulphur dioxide. The finding also relates to a strand of literature exploring the gap between WTP and WTA, where loss aversion is commonly used as an explanation for the WTP-WTA disparity (Lanz et al., 2009, Viscusi and Huber, 2012; Holte et al., 2016). In the study area of China, Yin et al. (2018) conducted a survey using CVM and found that the monetary compensation (i.e., WTA) for not implementing PM2.5 reduction policies is about two to three times larger than the WTP for implementing these policies

5.2.2 Further explanations regarding the insensitivity to the utility bill reduction

In Chapter 2, respondents were found to be insensitive towards the bill decreases, represented by an insignificant and negative parameter of the cost decrease variable. Taboo trade-off aversion and large ANA to the bill reduction were detected in this chapter, which suggests that moral concern may exist in taboo attribute trade-offs. Interestingly, the negative cost decrease variable is observed in all treatments used in this thesis (i.e., it is also found in Treatment 2 in Chapter 3 and Treatment 3 (i.e., the uncertain treatment) in Chapter 4), with the parameters in Treatment 2 and 3 even being significantly negative. A significant negative sign implies that respondents obtain disutility when bill decreases, which violates the basic assumption of monotonic preference in DCE (i.e., for an attribute, a "better" level is always preferred). The motivation behind this behaviour may also relate to ethics. Therefore, taboo trade-off aversion and cost ANA are investigated in Treatment 2 and Treatment 3, in order to see whether or not the evidence found in Treatment 1 is consistent with the results in the other two treatments.[51] The results suggest that a large percentage of ANA to the bill reduction and taboo trade-off aversion are found (see Table D.1, D.2, D.3 and D.4 in Appendix D.1).[52][53] As for the negative sign of the cost decrease variable, a possible explanation could be that respondents' moral concerns are much higher than their satisfaction from obtaining monetary compensation. This phenomenon is similar to the crowd-out effects observed in some lab experiments (Fehr and Gächter, 2000; Eckel et

[51] The results of the tests across treatments are assumed to be comparable, as the descriptions of the main attributes in all treatments are similar. Neither the additional risk attribute in Treatment 2 nor the risk framing in Treatment 3 is assumed to affect cost ANA or taboo trade-off aversion.

[52] The convergence issue occurs for some of the cost parameters when a 3-class model is assumed in the cost ANA analysis. Therefore, I apply a 2-class model for Treatment 2.

[53] As the current attribute levels do not appear in proposed new policies in Treatment 2 and Treatment 3, and thus the ASC term is suggested to be varied across classes (Glenk, Martin-Ortega, et al., 2015). Yet, I do not apply this specification for two reasons. First, the percentage of cost non-attendance reported in Treatment 2 and Treatment 3 are not too different from those in Treatment 1, where the current attribute levels are allowed to appear in new policy options. This consistency makes me believe that the inclusion of heterogeneous ASC across classes will not significantly affect the results. Second, I have tested models with both the cost decrease variable and ASC varying across classes. In 2-class models, the percentage of cost ANA is quite different from that assuming a homogenous ASC. It is concerned that the ANA to the cost decrease has been severely confounded with the effect of ASC in these 2-class models. Convergence issue is found for 3-class models where both the ASC and cost decrease variable are constrained to zero in an additional class to reflect the possibility of completely random choices made by respondents.

al., 2005), and field experiments for environmental goods (Vollan, 2008; d'Adda, 2011; Kits et al., 2014). In the latter studies, voluntary pro-environmental activities based on moral obligations are found to be crowded out after monetary rewards are introduced.

Additionally, this thesis also links the cost decrease variable with individual characteristics and a series of post-experimental questions to provide more insights on the counter-intuitive sign. The cost decrease variable in the asymmetric utility specification (Equation 2.3, Chapter 2) is interacted with some individual-level variables. Notably, the results show that those who reported themselves as not being able to accept air quality deterioration, suffer more disutility when bill is presented as a reduction (see Table D.5 in Appendix D.2).

Table 5.1 CVM studies on WTP for air quality improvement in China

	Sample size	**Region**	**Measured health effects**	**Change in air quality**	**Mean WTP (RMB/year/person)**
Pu et al. (2019)	9,744	Nationwide	Reduction in heavy pollution days	50%	275
Yin et al. (2018)	865	Beijing	Reduction in PM2.5 to the level of national class II	56%	2,286
Li & Hu (2018)	759	Jinchuan mining area	Air quality improvement in local area	n.a	102
Dong & Zeng (2018)	860	Beijing	Smog mitigation	45%	716
Wei & Wu (2017)	839	Jing-Jin-Ji Region	Reduction in severe PM2.5 polluting days	80%	602
Wang et al. (2016)	550	Jiangsu	Haze mitigation	n.a [a]	158
Sun et al. (2016)	903	Nationwide	Smog mitigation	n.a	1,590
Wang et al. (2015)	974	Shanghai	Pollution-related respiratory disease	n.a	466
Wang & Zhang (2009)	1,319	Ji’nan	Air quality improvement in local area	From class III to class II	100
Wang & Mullahy (2006)	482	Chongqing	Reduction in number of deaths	25%	14.3
Hammitt & Zhou (2006)	3,238	Three cities in China	Reduction in risk of death	86%	81,900

Note: (a) n.a means that the information of the magnitude of air quality improvement is not available.

Table 5.2 DCE studies on WTP for air quality improvement in China

	Sample size	Region	Measured health effects	Change in air quality	Mean WTP (RMB/year/person)[a]	Health most important?
Mao et al. (2020)	437	Harbin	Reduction in mortality	10%	385	Yes
Sergi et al. (2019)	1,060	Nationwide	Reduction in sulphur dioxide	30%	1,014	Yes
Yao et al. (2019)	319	Xi’an	Reduction in pollution level	From a severe polluted day to a clean day	24	/
Tang & Zhang (2015)	988	Nationwide	Reduction in mortality	50%	5,358	Yes

Note: (a) Only the WTP for the health effect is presented.

5.3 Policy and research recommendations

Air pollution has been significantly reduced since the central government enacted the China National Action Plan on Air Pollution Prevention and Control Plan. However, the sustainability of the policy implementation and the transparency of environmental data are still in doubt. Therefore, following the results of analysis, this thesis proposes the following recommendations for air quality management and for future research within the SP community.

Firstly, the restoration of blue skies over Beijing and its surrounding area (i.e., Jin-jin-ji region) was mainly achieved by a strong administrative power with a strong interest in air pollution control. Maintaining or enhancing the current stringent policies may harm economic growth, and thus the government has an incentive to relax air pollution controls. However, results of the loss aversion preference (Chapter 2) imply that there may be a significant loss of societal welfare if air quality deteriorates due to the relaxation of air pollution policy implementation. Therefore, the finding of this thesis would support the construction of a sustainable and long-term pollution reduction plan which balances economic development and air quality improvement, and aims to achieve a gradual but constant change in air quality. The success of such a plan requires inter-regional collaboration across local authorities and transparency in information sharing of environmental data. The plan also needs the participation of various stakeholders (e.g., citizens, NGOs and commercial organisations, etc.). Therefore, the government should raise public awareness about the adverse health effects of air pollution and encourage an eco-friendly lifestyle (e.g., commuting by public transport and using clean energy in residential heating in the rural areas). Environmental NGOs are found to positively affect China’s urban environmental governance (Li et al., 2018). Their roles in raising public awareness, monitoring local environmental incidents (e.g., reporting illegal pollution emissions from local factories) and the effectiveness of local environmental policies are irreplaceable. Thus, current laws should aim to encourage and assist the NGOs to take part in the long-term battle in air pollution reduction. Of course, further research from environmental scientist and managers would be necessary to see exactly how this would work out. However, this thesis offers a justification at the individual level for future air pollution policy.

Secondly, this thesis (in Chapter 2) shows that preference heterogeneity across social groups is non-negligible. Those who have high social capital tend to value the environment more than others. More interestingly, it is found that for some people, it seems that the environment cannot be traded for monetary goods. These messages imply that some social groups have stronger preferences for the environment, and trade-offs between environmental and monetary attributes are less relevant for them. It also implies that when economic growth is prioritized at the expense of local air quality, the government needs to realise that direct monetary compensation may not be an effective strategy, at least for certain groups. Non-monetary compensation, for example increasing the level of the provision of special health care to vulnerable groups, may be accepted by the public. However, the results could also imply that deteriorating air quality is simply non-compensatory.

Thirdly, policy outcomes are unlikely to be certain, and the results in Chapter 3 show that respondents have a preference for reducing the risk of the outcomes of air pollution policy, and this preference is independent of the associated environmental outcomes (i.e., a direct risk aversion preference). Under the assumption of risk neutrality, since a utility maximiser will only care about the expected outcomes of a policy, *ex post* welfare estimates can be adjusted by multiplying the probability attached to each outcome, and presenting the probability in the survey is irrelevant. However, the results of this thesis imply that the risk of outcome delivery itself is an important sphere that respondents will consider in decision making. Therefore, the information of risk should be included in SP design. From a policy point of view, investment in research should be made to enhance scientific understanding about the formation and evolution of air pollution in order to reduce uncertainty around the policy outcomes of air pollution.[54] Meanwhile, the central government needs to increase the efficiency of policy implementation in local areas – for example, legislating to reduce bureaucracy and prevent bribery and corruption.[55] This thesis (in Chapter 4) finds that in the uncertain treatment, where specific information about expected outcomes is given, respondents' preferences are not different from those in the certain treatment. This finding implies that for policy outcomes that are risky, the effects of presenting risk would be mitigated if risk (and its effect on environmental outcomes) were communicated properly.[56] As the average education level and numeracy skills of the public in China may be lower than those in developed countries, the government may have a particular need to convey the information of policy uncertainty in a very clear and simple way.

Reconciling the results from Chapter 3 and Chapter 4, it can be learnt that challenges in DCE design and the detection of decision rules under risk still exist for researchers who want to incorporate risk in DCE. The findings in Chapter 3 show that respondents consider information about risk in their decision making; however, this result may be attributed to the experimental design where outcomes and probabilities are separately presented (see detailed discussion in Section 3.6). For the second DCE design that involves risk (in Chapter 4), information about the outcomes and probabilities are

[54] For example, the government could provide financial support on research that aims to better simulate the air quality outcomes with different policy scenarios.

[55] Local governments are reported to commit corruption, or fabricate environmental data to deceive the pollution inspector appointed by the central government (see Xie (2019) for a news report and Wang et al. (2019) for an academic article on the effects of corruption on environmental quality in China). This implies that there is a risk that the stated policy outcomes would in fact not be achieved.

[56] A proper communication of risk means that the concept of probability and expected outcomes are well-described prior to and during the choice experiment, and that the assisting tools (e.g., the information of expected outcomes embedded in the DCE) that help to reduce respondents' cognitive burden are available.

combined in the same attribute, together with the expected values of the outcomes, and therefore the "separation effect" is eliminated. Results from the treatment comparison suggest that risk effects are insignificant. The findings from these two chapters together imply that respondents may consider risk as a standalone factor in DCE if it is visually highlighted as an independent attribute, but when a more efficient tool (i.e., expected values), which abridges both the information of probabilities and outcomes, is available, the importance of the probability itself is reduced. In this case, respondents may understand risk as a form of contextual uncertainty. To further understand to what extent respondents are affected by this separation effect, future researchers could design an experiment where environmental outcomes and probabilities are placed in the same attribute, but their levels are allowed to vary independently of each other. A comparison of model fit between this treatment design and a control design where risk and outcome are treated as separate attributes would unveil the extent of the attribute separation effect.

Another challenge of accommodating risk in DCE is to detect the behavioural rules that have been used by respondents in risky decisions. As shown in Chapter 3, model fit can be an effective statistic for the investigation of decision-making strategies, yet a more straightforward approach for future research is to apply eye-tracking technology. Eye-tracking method studies participants' eye moments (e.g., pupil size, saccades directions) when making choices, and informs researchers about information processing strategies used by respondents. Eye-tracking approach has been applied in DCE studies to understand various types of decision heuristics (Krucien et al., 2017; Chavez et al., 2018; Ryan et al., 2018). Regarding the risky choice scenarios presented in Chapter 3, with the availability of eye-tracking devices, an interesting avenue is to test whether top-to-bottom eye movement on the area where the health and the risk attributes are located (implying a behavioural rule that is consistent with expected utility theory), is more frequent than left-to-right eye movement (implying a direct risk aversion behaviour). For the risky choice scenarios presented in Chapter 4, by comparing the frequency of fixation on each information in the health attribute, eye tracking could help to explore whether respondents have considered all the information in this attribute (including the health outcomes, probabilities and the corresponding expected outcomes), or have only focused on a subset of the information.[57]

5.4 Limitations

5.4.1 Modelling limitation

5.4.1.1 Endogeneity and measurement error

[57] It is acknowledged that given the requirement of a moderate or large sample size in most DCE applications, the affordability and immobility of eye-tracking equipment may cause a challenge for the generalisation of this technique, yet a webcam-based eye-tracking system, which allows researchers to gather gaze data with relatively low cost, could be an encouraging alternative applied in DCEs (see Xu et al., 2015).

It is acknowledged that the issue of endogeneity may arise when socio-demographic and attitudinal questions are directly included in the choice model, as these variables may be correlated with unobservables. The endogeneity issue occurs when there are uncontrolled variables that simultaneously affect choices and those individual characteristic variables, and not accounting for this issue could affect the reliability of the estimated effects of individual-level variables. In Chapter 2, social capital indicators are linked with conditional estimates of air quality attributes which are closely related to choices of respondents. Although additional demographic variables were included as controls together with the social capital interactions in the main analysis, unobserved factors may still exist. A recent advancement is to use the hybrid choice model (Ben-Akiva et al., 2002). In the hybrid choice model, individual-specific variables are integrated as dependent variables instead of explanatory variables, together with stated choices. As those individual-level variables are treated independent of stated choices, endogeneity can be potentially mitigated (Daly et al. 2012). Another advantage of the hybrid choice model is that attitudinal variables are incorporated as functions of latent attitudes, in which error terms are specified to represent the stochastic parts of those attitudinal answers, and thus measurement errors can be reduced (Czajkowski et al., 2017). An increasing number of environmental studies integrate attitudinal variables using hybrid choice models (Hess and Beharry-Borg, 2012; Hoyos et al., 2015; Bartczak, Mariel, et al. 2016; Czajkowski et al., 2017; Boyce et al., 2019). Due to the unavailability of codes and time constraints, the hybrid choice model has not been used in this thesis, and this work is left to be done in the future.

5.4.1.2 The selection of random parameter distribution

There is no standard guidance for the selection of distributions for random parameters in mixed logit models, yet the priori choice of distribution has a significant impact on the preference estimates and WTPs (Hensher and Greene, 2003). In DCE applications, researchers make distributional assumptions based on both model fit comparisons and their expectations about the parameter signs. Parametric distributions such as normal and log-norm distributions are widely used, yet the inflexibility of the functional form may cause these distributions unable to provide good approximations to respondents' preferences.[58] Train and Sonnier (2005) have applied a bounded lognormal distribution (i.e., Johnson' SB distribution), in which two additional parameters that represent the location and the shape of the distribution are estimated. In addition, a semi-parametric distribution does not require any prior distributional assumptions by researchers, and is assumed to be more flexible, yet computationally

[58] For example, the symmetric feature of the normal distribution does not allow a good simulation of the preference estimates that are asymmetric around their means. Additionally, researchers may obtain a considerable number of preference estimates with counter-intuitive signs if the standard deviations of the normally distributed parameters exceed their means (Bansal et al., 2018). Lognormal distributions solve the problem as exponentiated parameters have to be in either the positive or the negative domain, yet this distribution suffers from fat tails.

more demanding. Fosgerau and Mabit (2013) proposed to use Legendre polynomials, in which flexibility can be achieved by adding the power series of a common parametric distribution (e.g., uniform or normal distribution). A more generalized semi-parametric distribution is the logit-mixed logit model proposed by Train (2016). The mixing distribution applies polynomials, splines, steps functions or a combination of them in model approximations, and the shape of the distribution is specified by researchers.

In this thesis, in order to test the robustness of the results obtained from mixed logit models, models of random parameters with a log-normal distribution, Johnson SB distribution, or normal distribution with a second-order polynomial have been tested. The model fits of these models are compared with the model fit of the model following a normal distribution. In general, random parameters assuming log-normal distributions are hard to converge, and those that are converged suffer from the issue of exploding parameters (i.e., attributes with unrealistically high mean parameters). This issue has also been reported in Chiou and Walker (2007) and Hole (2011c). Assuming a Johnson SB distribution or a normal distribution with a second-order polynomial has been found to improve the model fit, yet only if these alternative distributions are not applied to all random parameters; convergence issue occurs when all random parameters are assumed to follow such distributional assumptions. Due to the unavailability of codes and time constraints, logit-mixed logit has not been applied in this thesis, and the work is left to be done in the future.

5.4.2 Experimental limitation

5.4.2.1 Measuring institutional trust

It is acknowledged that in measuring social capital, institutional trust is an important aspect and has been reported to correlate with preferences for coastal management, water quality and environmental improvement in general (Jones, Malesios, et al., 2009; Jones, Clark, and Malesios, 2015; Polyzou et al., 2011). Questions typically involve eliciting the level of trust that respondents have in local, regional and central governments with regards to the effectiveness of environmental and financial management. Unfortunately, in this thesis, those questions could not be included in the survey as the marketing company (and any other marketing company contacted) refused to collect such information due to conflict of interests.

5.4.2.2 The selection of survey modes

It is acknowledged that this thesis could have collected data of better quality at the stage of pre-tests and in formal data collection if a greater budget had been available. First, although questionnaire pre-testing was conducted before the formal data collection, more participants, especially those from

Beijing (the study area of the thesis), would have been invited if funding had been sufficient (see Appendix D.3 for the detailed procedure of the pre-tests). Second, data were collected through an online survey system in this thesis. A growing number of studies choose to conduct the DCEs online (Determann et al., 2017). Compared with traditional survey modes (e.g., face-to-face interviews and telephone surveys), an Internet-based survey has the advantage of rapid data collection with lower costs (Ryan et al., 2020). However, this data collection method has been criticized by survey methodologists for its low representativeness, reliability and non-response bias. A typical issue, which occurs in this thesis, is the coverage error. The findings of this thesis suggest that the respondents tend to be younger and more educated than the general population, which is consistent with other studies that use internet surveys in their DCEs (Olsen, 2009; Grandjean et al., 2009). However, Lindhjem and Navrud (2011) have reviewed 17 SP environmental studies that compared different survey modes in their data collection and have concluded that in general, despite the disadvantages of the Internet-based survey stated above, little evidence suggests significant WTP disparity between different survey modes.[59] In terms of reliability, Lindhjem and Navrud (2011) also point out that lower data quality from Internet surveys has not been verified on a large scale. Watson et al. (2019) find that perceived consequentiality (i.e., to what extent respondents think that the policy they have chosen will be achieved) for a computer-based survey is significantly higher than that for a mail survey. For future research, instead of focusing on the differences in welfare estimates between survey modes, reasons for these disparities should also be explored.

5.4.2.3 Current levels do not appear in policy alternatives

In Treatment 2 (in Chapter 3) and Treatment 3 (i.e., the uncertain treatment in Chapter 4), current levels of attributes are only allowed to appear in the status quo options, but not in the new policy options. Although hypotheses are still able to be tested in these settings, respondents' preferences for the first level (i.e., the lowest level) of increase/decrease in attributes, relative to the current level, cannot be explicitly tested. In this case, the alternative specific constant captures the utility differences between the first levels of attributes in new policy options and the current levels of attributes in the status quo option, in addition to utility from choosing the status quo option for reasons that are unrelated to attributes (Glenk, Martin-Ortega, et al., 2015). Therefore, results for Treatment 2 and Treatment 3 are based on the assumption that preference for the first level changes (relative to the current attribute levels) in both the gain and the loss domains is not dramatic. Violation of this assumption, however, is unlikely to occur based on the observation from Treatment 1 (Chapter 2), where current levels in the status quo option are allowed to appear in proposed policy options. The

[59] A more recent study finds a significant smaller WTP for an Internet-based survey than that for a mail survey (Boyle et al., 2016).

results from Treatment 1 suggest that respondents prefer (dislike) health to be improved (deteriorated) from the current level to the first level of improvement (deterioration), and the preference (distaste) is smaller than that for the second level of improvement (deterioration). It should be noted that although the design also differs across treatments in terms of the provision of the additional information on risk, the difference is unlikely to affect respondents' preferences for changes in attributes from the current levels to the first proposed levels.

5.4.2.4 Individual-specific status quo options

In the experiments carried out, current levels of attributes are estimated and defined so that they represent future air pollution conditions if current policy implementation is maintained, this situation differs from studies where self-defined status quo levels are incorporated (Barton and Bergland, 2010; Glenk, 2011; Ahtiainen et al., 2015). In these studies, current levels are defined as individual-specific, reflecting respondents' practical perception or experience of estimated environmental goods. The design may increase credibility of the survey and reduce protest responses, as individual perceptions of the current situations of the environmental good are reflected in the experiment. However, the reason for using uniform status quo levels across individuals in this thesis is that the current air pollution conditions across different areas in Beijing are mostly homogenous. Therefore, the difference of estimates from researcher-defined and self-defined current levels is expected to be trivial. More importantly, it is highly unlikely that individuals know the current levels of air pollution and are able to define the status quo accurately. A wrongly defined status quo may lead to biased preference estimates (e.g., too extreme, if most respondents (wrongly) state their current perception of air quality as "very bad"). In addition, technological difficulties were encountered during the process of data collection in this thesis. Presenting an individual-specific status quo option together with other policy options could not be achieved under the web-survey system of the marketing company with which the researcher collaborated. Hence, using fixed attribute levels in the status quo option in this context is considered to be reasonable.

5.5 General conclusion

Based on current air quality conditions, available policies and the effects of air pollution described in the literature, this thesis provides a gain-loss framework that aims to elicit individuals' preference and welfare estimates, when both air quality improvement and deterioration scenarios are presented in policy options, using discrete choice experiments.

Firstly, this thesis (in Chapter 2) tests the existence of loss aversion in air quality attributes and explores the effects of social capital on air quality preferences, and the link between loss aversion and social capital. This thesis also investigates whether or not ethical considerations are involved in decision making. This has been done by testing non-attendance to the cost attribute and the presence of taboo trade-off aversion. Significant relationships between social capital and air quality changes are detected. People are found to give greater weight to disutility from air quality deterioration than utility from air quality improvement, and this effect varies according to the person's level of social capital. A considerable number of respondents are found to have ignored the variation in cost in environmental deterioration scenarios. In addition, I also provide evidence suggesting the presence of taboo trade-off aversion.

Secondly, this thesis (in Chapter 3) extends the investigation into a risky sphere where policy outcomes are specified as probabilistic. In the first experimental design that involves risk, risk is embedded as an independent attribute, representing the likelihood of achieving the corresponding environmental outcomes. Different model specifications are examined with underlying behavioural assumptions, and the one that can best approximate respondents' choices in the experiment is selected. The main findings support the best performance of the direct risk aversion specification, which implies that respondents evaluate risk separately from its associated policy outcome.

Lastly, this thesis (in Chapter 4) explores a specific framing effect, namely risky choice framing, using a between-subject design. In one sample, policy outcomes for a DCE are specified as risky, whilst the outcomes are certain in another sample. The expected outcomes in both experiments are designed to be equal to allow for a pure estimation of risky choice framing. Moreover, for the same expected outcome, probabilities could differ in size, which enables the investigation of probability-dependent risk effects. The finding is that respondents are not affected by the risky choice framing, and this result does not change when the size of the probability presented in policy scenarios changes.

Motivated by prospect theory and other theories of economic decision making, this thesis attempts to incorporate concepts from behavioural economics into the fields of stated preferences and environmental economics. The results altogether support the idea that individuals' preferences for environmental goods could be affected by the gain-loss framing, and respondents are likely to use simplified strategies in decision making when experimental scenarios are relatively complex (e.g., a scenario that involves outcome uncertainty). To further explore the effects of framing and heuristic strategies in stated preference literature, future studies could link these effects with various survey engagement indicators that show respondents' choice consistency, certainty and understanding of the context, which will help to better understand the effects of framing and heuristics. Concerning the effects of framing and heuristic decision making on utility, one caveat is that both an individual's scale and preference can be channels of these effects, yet the scale and the preference coefficient cannot be separately identified under the random utility maximization framework (Hess and Ross, 2012; Hess and Train, 2017). Therefore, future research aiming to relate framing and decision heuristics to preference or WTP estimates should first mitigate the bias arising from the inseparable scale and preference parameters. One potential solution is to treat survey engagement indicators (e.g., self-reported level of understanding of the experiment and self-reported choice certainty, etc.) as proxies for the scale of utility, and control for these indicators in utility function under a hybrid choice framework (see Hess and Stathopoulos (2013)). In addition, to understand whether some people are more likely to be affected by the framing effects or to use heuristics than others, it will also be interesting to link these effects with various socioeconomics characteristics, environmental attitudes and psychological factors.

Appendices

Appendix A: Appendix for Chapter 2

Appendix A.1: Calculation of the current levels of the attributes

(1) Health attribute

There is no data available in terms of the number of hospital admission in Beijing due to air pollution. The current level of hospital admission due to air pollution in Beijing is calculated by multiplying the number of general hospital admission by a coefficient called the total transformation rate, which indicates the relationship between general hospital admission and air pollutants. The relationships are shown below in Equations A.1:

$$N(admission)_{air} = N(admission)_{gen} \times TR_{total} \tag{A.1}$$

$N(admission)_{air}$ represents the number of hospital admissions due to air pollution, $N(admission)_{gen}$ represents the number of general hospital admissions, and TR_{total} represents the total transformation rate (i.e., the percentage change of general hospital admission given the change of ambient air pollutants). TR_{total} is the weighted average of the current pollution level of a specific air pollutant multiplied by the pollutant-specific transformation rate (measured by an X% increase of general hospital admissions due to every 10ug/m3 increase of the air pollutant).

General hospital admissions in 2017 in Beijing were 589 thousand, according to the Beijing Municipal Environmental Protection Bureau. The air pollutants and their corresponding transformation rates can be found in Table A.1. For example, general hospital admissions increased by 0.23% given an increase of 10ug/m3 of PM2.5, and the current level of PM2.5 was 52.5, so $TR_{PM2.5}$ is $\frac{52.5}{10} \times 0.23\%$. Similar calculation process can be done for the rest of the pollutants, and the general transformation rate will be the average of all the pollutant-specific transformation rates. The final estimate of the number of hospital admissions in Beijing due to air pollution in 2017 is about 130,000. The level is comparable to that in other regions where data are available, and respondents in the pre-test sample have reported that the current level of health stated in the choice experiment is realistic.[60]

[60] The initial design uses number of deaths due to air pollution as a health attribute. However, some respondents in pre-tests expressed depression and stress when making a trade-off between human lives and money. They reported that human lives should be invaluable and shouldn't be exchanged for money. To mitigate this issue, hospital admissions have been used, instead of deaths, which is thought to be less upsetting. In a subsequent pre-test, respondents did not express a strong opposition to the new health attribute.

Table A.1 Air pollutants and corresponding transformation rates

Air Pollutants	Transformation rates	Current levels	References
PM2.5	0.23%	52.5	Xu et al. (2016)
PM10	0.88%	5.5	Zhang et al. (2015)
SO2	0.76%	42.7	Zhang et al. (2015)
NO2	1.82%	84.7	Zhang et al. (2015)
O3	0.33%	160.5	Tian et al. (2018)

(2) Visibility attribute

In this study, number of "bad visibility days" is used to describe the visibility attribute. "Bad visibility" is defined as the months with PM2.5 level above the 75th percentile of the year (Rizzi, 2014). It is found that 3 out of 12 months have PM2.5 level higher than the 75^{th} percentile in Beijing in 2017. Therefore, the average number of "bad visibility days" in a month would proportionally be 30*1/4≈ 8days/month.

(3) Cost attribute

The mean percentage of GDP loss due to air pollution is 2.5% according to The World Bank (The World Bank, 2007). GDP per head is calculated as China's total GDP in 2017 divided by China's overall population in 2017. The estimated individual cost due to air pollution is the GDP per head multiplied by the percentage GDP loss due to air pollution. The initial cost range is [-100,100] RMB per month, but in pre-tests it was found that respondents thought the levels were too low to take account of, partly because citizens in Beijing are richer than the average in China. Therefore, the cost range was repeatedly increased until respondents stated that the cost was large enough to be considered; this final cost change is [-500, 500] RMB per month.

Appendix A.2: Social capital questions

Social trust questions

1. Two general social trust questions

Do you agree or disagree the following statement? (1 is strongly disagree; 2 is slightly disagree; 3 neither agree nor disagree; 4 is slightly agree and 5 is strongly agree)

(1) Generally speaking, most people in my city can be trusted
(2) Most people in my city would try to take advantage of me if they got the chance

2. Two context-specific social trust questions

Do you agree or disagree the following statement? (1 is strongly disagree; 2 is slightly disagree; 3 neither agree nor disagree; 4 is slightly agree and 5 is strongly agree)

(1) I trust that other citizens in my city will contribute money to improve the air quality if they have chance
(2) I trust that other citizens do not want to sacrifice the air quality in my city to gain personal benefits if they have chance

Social norms questions:

1. One general social norm question

Please tell me the following statement about whether you think they are acceptable in the city you live? (1 is strongly acceptable; 2 is somewhat acceptable; 3 neither acceptable nor unacceptable; 4 is somewhat unacceptable and 5 is strongly unacceptable)

a) Cheating on taxes if people have a chance

2. Two context-specific social norm questions (Descriptive and injunctive norms question)

(1) According to you, what percentage of citizens in your city will contribute their time and (or) money on air quality improvement, although the individual effort is limited to the problem.

a) Most of them
b) Some of them
c) Little of them

(2) Please tell me whether you agree or not about the following statements. (1 is strongly disagree; 2 is slightly disagree; 3 neither agree nor disagree; 4 is slightly agree and 5 is strongly agree)

a) People who are important to me think I should contribute my time and (or) money on air quality, although the individual effort is limited to the problem.

3. One personal norm question

(1) Please tell me whether you agree or not about the following statements. (1 is strongly disagree; 2 is slightly disagree; 3 neither agree nor disagree; 4 is slightly agree and 5 is strongly agree)

(a) People have obligation to use clean energy for central heating (if they are affordable) in winter in my city.

Social networks (information) questions:

1. Two social networks questions

(1) How often have you heard anyone (friends, relatives or colleagues/classmates) talking about the health and (or) visibility effects of air pollution in China? (Often/Sometimes /Never/I don’t know)

(2) Do you think you know enough about air pollution (air pollutants, effect of air pollution and air-pollution related policies) through social media or people surrounding you? (I know quite a lot/I have some of knowledge about it/I know little about it)

Appendix A.3: Factor analysis

Table A.2a, A.2b and A.2c show the results of factor analysis using the extraction method of principle-component analysis, and the results of rotation sums of squared loadings using the orthogonal varimax method. The eigenvalue shows the variance of each factor, and the proportion of the sums of squared loadings shows the percent of total variance each factor is accounted for. The rotation sums of squared loadings are variances after rotation. As I use orthogonal varimax rotation, factors are not allowed to be correlated.

Results from the eigenvalues (variance of the factor) of each table show that Factor 1a and Factor 2a are sufficient to represent the social trust indicator as the eigenvalues of these two factors are larger than 1. Similarly, Factor 1b and Factor 2b are sufficient to represent the social norm indicator, [61] and Factor 1c is sufficient to represent the social networks (information) indicator. Additionally, as for the results of rotation sums of squared loadings, I use the proportion of total variance of each factor as their weights and calculate the index for each social capital indictor. For example, the variance of Factor 1 and Factor 2 in social trust indicator (Table A.2a) account for 42.93% and 28.58% of the total variance respectively. Thus, the social trust indicator is equal to the weighted sum of each factor (i.e., social trust indicator = (42.93%*factor1+28.58%*factor2)/(42.93%+28.58%)). The method is also applied to calculate the social norms and social networks (information) indictors.

Finally, each social capital indicator is divided to two groups according to their median values, and dummy variables are created to represent these indicators. For example, the dummy variable of social trust is equal to 0 if individuals' social trust indicator is lower than its median, and is equal to 1 if individuals' social trust indicator is higher than its median. The method is also applied to calculate the social norms and social networks (information) dummies.

[61] The eigenvalue of Factor 2b is 0.925, which is lower than 1, however, I do not want to drop this factor as it accounts for 23% of the total variance. Thus, I relax the standard and allows this factor to represent the social norm indicator together with Factor 1b.

Table A.2a Factor analysis using the principle-component analysis for the social trust indicators

	Sums of squared loadings			Rotation sums of squared loadings		
Factors	**Eigenvalue**	**Proportion**	**Cumulative**	**Variance**	**Proportion**	**Cumulative**
Factor 1a	1.798	0.449	0.449	1.71706	0.4293	0.4293
Factor 2a	1.063	0.266	0.715	1.14338	0.2858	0.7151
Factor 3a	0.622	0.156	0.871			
Factor 4a	0.518	0.129	1.0000			
Model statistics						
LR test: independent vs. saturated: chi2(6) = 3353, Prob>chi2 = 0.000						

Table A.2b Factor analysis using the principle-component analysis for the social norms indicators

	Extraction sums of squared loadings			Rotation sums of squared loadings		
Factors	**Eigenvalue**	**Proportion**	**Cumulative**	**Variance**	**Proportion**	**Cumulative**
Factor 1b	1.722	0.431	0.431	1.415	0.354	0.354
Factor 2b	0.926	0.231	0.662	1.232	0.308	0.662
Factor 3b	0.740	0.185	0.847			
Factor 4b	0.613	0.153	1.0000			
Model statistics						
LR test: independent vs. saturated: chi2(6) = 2242, Prob>chi2 = 0.000						

Table A.2c Factor analysis using the principle-component analysis for the social networks indicators

	Extraction sums of squared loadings			Rotation sums of squared loadings		
Factors	**Eigenvalue**	**Proportion**	**Cumulative**	**Variance**	**Proportion**	**Cumulative**
Factor 1c	1.171	0.586	0.586	1.171	0.586	0.586
Factor 2c	0.829	0.414	1.0000			
Model statistics						
LR test: independent vs. saturated: chi2(6) = 205, Prob>chi2 = 0.000						

Appendix A.4: H3a and H3b testing for the social network (information) index

Table A.3 OLS regressions of conditional estimates on social network (information) index

					Full sample		Partial sample	
Variables [b]	$\mathbf{H^{imp}}$ [a]	$\mathbf{H^{det}}$	$\mathbf{V^{imp}}$	$\mathbf{V^{det}}$	$\mathbf{LA^{health}}$	$\mathbf{LA^{visibility}}$	$\mathbf{LA^{health}}$	$\mathbf{LA^{visibility}}$
Social network	0.068	-0.423**	0.002	-0.051**	-3.622	-0.785**	-0.134	-0.745**
	(0.084)	(0.174)	(0.003)	(0.021)	(5.334)	(0.313)	(0.555)	(0.320)
Age	-0.057	-0.025	-0.001	0.010	2.543	0.163	0.252	0.173
	(0.053)	(0.111)	(0.001)	(0.012)	(3.086)	(0.155)	(0.329)	(0.158)
Income	0.072***	-0.115**	0.000	0.010	0.720	0.194**	-0.172	0.206**
	(0.025)	(0.054)	(0.001)	(0.010)	(1.406)	(0.090)	(0.181)	(0.092)
Gender	-0.096	0.015	0.003	-0.019	-1.501	-0.144	0.171	-0.123
	(0.076)	(0.150)	(0.002)	(0.017)	(5.653)	(0.233)	(0.512)	(0.261)
Education	-0.138	0.378*	-0.002	0.034	3.771	0.413	-0.067	0.475
	(0.111)	(0.218)	(0.003)	(0.029)	(3.385)	(0.350)	(0.637)	(0.353)
Constant	0.978**	-1.150	0.071***	-0.352***	-22.260*	-5.275***	-1.048	-5.625***
	(0.411)	(0.835)	(0.011)	(0.095)	(11.38)	(1.176)	(2.256)	(1.184)
Model statistics								
n(observations)	226	226	226	226	226	226	219	219
R-squared	0.044	0.053	0.012	0.049	0.005	0.065	0.009	0.067

Note: (a) H^{imp}, H^{det}, V^{imp} and V^{det} represent individual-level conditional means; H^{imp} (H^{det}) represents the health attribute in the gain (loss) domain, and V^{imp} (V^{det}) represents the visibility attribute in the gain (loss) domain; LA^{health} ($LA^{visibility}$) is the loss aversion index of the health (visibility) attribute; (b) Social network is a dummy variable, equalling to 1 for the high social network group and equalling to 0 for the low social network group; Age is the midpoints of ranges of respondents' age (in year); Income is a categorical variable that represents the midpoints of ranges of respondents' annual incomes (in RMB); Gender is a dummy variable taking the value 1 for male and 0 for female; Education is respondents' highest education level; (c) Standard errors of the means in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix A.5: Robustness check of H3a and H3b

Table A.4a OLS regressions of conditional estimates on different social capital indicators (the medium group is omitted)

	$\mathbf{H^{imp}}$ [a]			$\mathbf{H^{det}}$			$\mathbf{V^{imp}}$			V^{det}		
Variables [b]	Social trust	Social norms	Social network	Social trust	Social norms	Social network	Social trust	Social norms	Social network	Social trust	Social norms	Social network
Social trust	0.097*			-0.302***			0.002			-0.009		
	(0.052)			(0.106)			(0.001)			(0.012)		
Social norms		0.277***			-0.422***			0.001			0.004	
		(0.048)			(0.103)			(0.001)			(0.012)	
Social network			0.017			-0.050			0.000			-0.010
			(0.053)			(0.113)			(0.002)			(0.013)
Age	-0.034	-0.024	-0.128*	0.008	-0.106	0.077	-0.002	-0.000	-0.002	0.010	0.013	0.020
	(0.060)	(0.054)	(0.070)	(0.141)	(0.120)	(0.135)	(0.001)	(0.001)	(0.002)	(0.015)	(0.013)	(0.019)
Income	0.053	0.025	0.058*	-0.096	0.016	-0.134*	0.001	0.001	0.000	0.000	0.003	-0.006
	(0.033)	(0.029)	(0.030)	(0.073)	(0.069)	(0.073)	(0.001)	(0.001)	(0.001)	(0.007)	(0.008)	(0.009)
Gender	-0.004	-0.189**	-0.080	-0.121	0.092	0.068	0.002	0.003	0.000	-0.016	-0.020	-0.009
	(0.087)	(0.079)	(0.091)	(0.172)	(0.161)	(0.192)	(0.002)	(0.003)	(0.003)	(0.020)	(0.021)	(0.021)
Education	-0.242**	-0.246**	-0.172	0.551**	0.375	0.326	-0.0001	0.003	0.002	0.050	0.013	0.030
	(0.110)	(0.102)	(0.133)	(0.271)	(0.256)	(0.267)	(0.003)	(0.003)	(0.003)	(0.032)	(0.033)	(0.035)
Constant	1.135***	1.347***	1.339***	-1.623	-1.660*	-1.403	0.067***	0.051***	0.070***	-0.383***	-0.301***	-0.321***
	(0.417)	(0.393)	(0.487)	(0.983)	(0.911)	(1.014)	(0.011)	(0.011)	(0.012)	(0.103)	(0.105)	(0.122)
Model statistics												
n(observations)	151	153	126	151	153	126	151	153	126	151	153	126
R-squared	0.073	0.252	0.046	0.110	0.143	0.035	0.041	0.034	0.016	0.031	0.017	0.020

Note: (a) $\mathrm{H^{imp}}$, $\mathrm{H^{det}}$, $\mathrm{V^{imp}}$ and $\mathrm{V^{det}}$ are the individual-level conditional estimates; $\mathrm{H^{imp}}$ ($\mathrm{H^{det}}$) is the health attribute in the gain (loss) domain, and V^{imp} (V^{det}) is the visibility attribute in the gain (loss) domain. (b) Social trust, Social norms and Social network are the dummy variables, equalling to 1 for the high social trust, norms or network group and equalling to 0 for the low social trust, norms or network group; Age is the midpoints of ranges of respondents' age (in year); Income is a categorical variable that represents the midpoints of ranges of respondents' annual incomes (in RMB); Gender is a dummy variable taking the value 1 for male and 0 for female; Education is respondents' highest education level; (c) Standard errors of the means in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A.4b OLS regressions of loss aversion indices on different social capital indicators (the medium group is omitted)

	Full sample						Partial sample					
	LA^{health} [a]			$LA^{visibility}$			LA^{health}			$LA^{visibility}$		
Variables [b]	Social trust	Social norms	Social network	Social trust	Social norms	Social network	Social trust	Social norms	Social network	Social trust	Social norms	Social network
Social trust	-2.629			-0.039			-0.211			-0.042		
	(4.085)			(0.164)			(0.296)			(0.168)		
Social norms		-3.234			0.167			-0.557			0.167	
		(3.877)			(0.171)			(0.373)			(0.176)	
Social network			1.917			-0.122			0.093			-0.098
			(1.868)			(0.167)			(0.372)			(0.170)
Age	1.961	2.394	-1.580	0.122	0.202	0.233	-0.078	0.128	0.043	0.110	0.201	0.254
	(3.855)	(3.583)	(2.600)	(0.196)	(0.184)	(0.240)	(0.343)	(0.380)	(0.473)	(0.202)	(0.188)	(0.241)
Income	1.011	1.572	1.462	0.053	0.091	-0.076	-0.294	-0.045	-0.242	0.059	0.101	-0.065
	(1.587)	(1.526)	(1.954)	(0.093)	(0.115)	(0.113)	(0.233)	(0.231)	(0.276)	(0.095)	(0.117)	(0.118)
Gender	-0.996	-0.022	5.370	-0.233	-0.125	-0.093	0.198	0.470	0.305	-0.188	-0.069	-0.018
	(6.858)	(6.421)	(4.245)	(0.270)	(0.290)	(0.283)	(0.588)	(0.687)	(0.754)	(0.324)	(0.344)	(0.338)
Education	0.443	1.028	0.549	0.766*	0.350	0.480	-0.167	0.360	-0.143	0.721*	0.299	0.595
	(3.124)	(3.026)	(4.392)	(0.406)	(0.422)	(0.446)	(0.637)	(0.702)	(0.891)	(0.416)	(0.432)	(0.449)
Constant	-12.95	-20.40*	-14.20	-5.785***	-5.422***	-4.611***	1.015	-2.788	-0.300	-5.698***	-5.394***	-5.231***
	(10.19)	(11.32)	(13.67)	(1.296)	(1.336)	(1.519)	(2.078)	(2.687)	(2.999)	(1.338)	(1.395)	(1.520)
Model statistics												
n(observations)	151	153	126	151	153	126	145	147	122	145	147	122
R-squared	0.004	0.006	0.034	0.040	0.032	0.020	0.029	0.021	0.012	0.034	0.029	0.024

Note: (a) LA^{health} ($LA^{visibility}$) is the loss aversion index of the health (visibility) attribute. (b) Social trust, Social norms and Social network are the dummy variables, equalling to 1 for the high social trust, norms and network group and equalling to 0 for the low group; Age is the midpoints of ranges of respondents' age (in year); Income is a categorical variable that represents the midpoints of ranges of respondents' annual incomes (in RMB); Gender is a dummy variable taking the value 1 for male and 0 for female; Education is respondents' highest education level; (c) Standard errors of the means in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix A.6: Additional results for the ECLC model

Table A.5 Additional results for the ECLC models with two and four classes

	ECLC Cost Increase		**ECLC Cost Decrease**	
Variables [a]	**Two classes**	**Four classes**	**Two classes**	**Four classes**
ASC SQ	-0.584***	-0.584***	-0.543***	-0.504***
	(0.126)	(0.128)	(0.124)	(0.127)
H^{imp}	0.450***	0.469***	0.407***	0.421***
	(0.062)	(0.063)	(0.061)	(0.062)
H^{det}	-0.364***	-0.369***	-0.306***	-0.333***
	(0.064)	(0.065)	(0.063)	(0.065)
V^{imp}	0.088***	0.097***	0.084***	0.088***
	(0.029)	(0.030)	(0.029)	(0.029)
V^{det}	-0.069**	-0.069**	-0.051*	-0.058**
	(0.029)	(0.030)	(0.029)	(0.029)
C^{inc}			-0.001***	-0.001***
			(0.000)	(0.000)
C^{dec}	-0.001***	-0.001***		
	(0.000)	(0.000)		
Classes and probabilities [b]				
Class 1 (Cost ANA)	0	0	0	0
Class 2	-0.013***	-0.007***	-0.007***	-0.016*
	(0.002)	(0.002)	(0.002)	(0.009)
Class 3		-0.035***		0.004***
		(0.014)		(0.002)
Class 4		0.021		-0.003
		(0.018)		(0.002)
π^1	0.82*** [c]	0.74	0.70***	0.30
	(0.04)		(0.05)	
π^2	0.18***	0.18	0.30***	0.10
	(0.04)		(0.05)	
π^3		0.06		0.17
π^4		0.02		0.43

Table A.5: Continued

Model statistics				
Log-likelihood	-2273	-2264	-2301	-2285
BIC	4609	4620	4664	4662

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; $\mathrm{H}^{\mathrm{imp}}$ ($\mathrm{H}^{\mathrm{det}}$) is the health attribute in the gain (loss) domain; $\mathrm{V}^{\mathrm{imp}}$ ($\mathrm{V}^{\mathrm{det}}$) is the visibility attribute in the gain (loss) domain; $\mathrm{C}^{\mathrm{inc}}$ ($\mathrm{C}^{\mathrm{dec}}$) is the cost attribute when the bill is specified as increase (decrease); (b) Class 1 (Cost ANA) is the coefficient for the cost ANA class, with its corresponding class probability being π^1; Class 2, 3 and 4 are the coefficients for the attended cost classes, and the probabilities of class attendance are π^2, π^3 and π^4, respectively. (c) The standard error of the class probabilities are calculated using the Delta method. Due to code unavailability, the standard errors of class probabilities for the models with more than three classes are unable to be calculated (d) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix A.7: Additional taboo trade-off aversion results

Table A.6 The attribute-specific taboo (health) model with individual characteristic interactions

Variables [a]	Mean	S.D.
C^{inc}	-0.0016***	
	(0.0003)	
C^{dec}	-0.0003	
	(0.0004)	
ASC SQ	-1.361***	1.483***
	(0.198)	(0.169)
H^{imp}	0.593***	1.093***
	(0.113)	(0.122)
H^{det}	-0.913***	1.509***
	(0.156)	(0.155)
V^{imp}	0.059	-0.143**
	(0.038)	(0.056)
V^{det}	-0.190***	0.327***
	(0.044)	(0.048)
Taboo Penalty	-0.291	-1.578***
	(1.886)	(0.242)
Interactions between the taboo term and individual characteristics		
Age	0.120	
	(0.243)	
Income	-0.072	
	(0.128)	
Gender	0.004	
	(0.347)	
Education	0.313	
	(0.483)	
Not accepting air deterioration	-0.686*	
	(0.389)	

Table A.6 Continued

Ignore cost	-0.542
	(0.587)
Social trust	-0.348
	(0.382)
Social norm	-1.323***
	(0.395)
Model statistics	
Log-likelihood	-1977
BIC	4147

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; $\mathrm{H}^{\mathrm{imp}}$ ($\mathrm{H}^{\mathrm{det}}$) is the health attribute in the gain (loss) domain; $\mathrm{V}^{\mathrm{imp}}$ ($\mathrm{V}^{\mathrm{det}}$) is the visibility attribute in the gain (loss) domain; $\mathrm{C}^{\mathrm{inc}}$ ($\mathrm{C}^{\mathrm{dec}}$) is the cost attribute when the bill is specified as increase (decrease); Taboo Penalty is the taboo term capturing the preference for taboo trade-off aversion; Age is the midpoints of ranges of respondents' age (in year); Income is a categorical variable that represents the midpoints of ranges of respondents' annual incomes (in RMB); Gender is a dummy variable taking the value 1 for male and 0 for female; Education is respondents' highest education level; Not accept air deterioration is the self-reported unacceptance of air quality deterioration scenarios (equals 1 if reported deterioration scenario is unacceptable, and 0 if acceptable); Ignore cost is the self-reported ignoring of the cost attribute (equals 1 if a respondent stated to have ignored the cost attribute, and 0 if not); Social trust (Social norms) is a dummy variable equals to 1 if the respondent is in the high social trust (social norms) group and equal to 0 if she is in the low social trust (social norms) group. (b) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix B: Appendix for Chapter 3

Appendix B.1: Robustness checks

B.1.1: Additional test for non-nested models

I also use the J-test (Davidson-MacKinnon, 1981) to compare the model fit of the two non-nested models: the DU and the EU models. Results from the J-test suggest that the DU model fits the data better. The fitted-value term from the DU model has significant impact (z-value=8.15) as a covariate in the EU model, whilst it is not the case for the opposite test.

B.1.2: Different distributional assumptions for the random parameters

I test whether the DU specification performs better when imposing other distributional assumptions (i.e., log-normal, symmetric triangular or Johnson SB distribution) on the health and risk attributes instead of normal distributions. 500 Modified Latin Hypercube Sampling (MLHS) draws are used for those distributional assumptions. Results indicate that for models that are successfully converged, the DU specification still outperforms the other models. For Research Question 1, I also test whether results are robust with higher number of draws (2000 Halton draws), and results still suggest a better model fit for the DU specification.

B.1.3: Non-linear value function specifications

An additional parameter is estimated for the health attribute in the EU specification in the gain domain to account for nonlinearity. A power functional form is used to measure the concavity of the value function, which is calculated as $\frac{(\mathrm{H}^{\mathrm{imp}})^{1-\alpha}}{1-\alpha}$ (Holt and Laury, 2002). $\alpha>0$ implies a concave value function and $\alpha=0$ implies linear value function. The results suggest that $\alpha=0.08$, and the model fit of the non-linear specification (BIC=6019) is still worse than that of the DU specification. Additionally, I test if allowing for nonlinearity in the value function counterbalances the effect of the independent risk, by adding an independent risk attribute in the non-linear EU specification in the gain domain, as discussed in Glenk and Colombo (2013). The results show that the independent risk attribute is still significant (p-value=0.04).

A more complicated PT specification is estimated, with the health attribute being assumed to be non-linear in the gain domain. The results show a slightly concave value function (α=0.16) and an inverse-S shape weighting function (γ=0.49), with the BIC value equalling to 6012. The model fit of the non-linear PT specification is similar to its linear counterpart, yet it does not outperform that of the DU specification. It is also found that if adding an additional independent risk attribute to the non-linear PT specification, the newly-added risk parameter is still significant (p-value=0.01). These results suggest that specifying the value function as linear or non-linear does not affect the conclusion that DU specification has the best statistical performance in this study.

B.1.4: Partial expected utility specifications

In addition to the traditional expected utility specification, respondents may also consider attributes with partial expected utility (Partial-EU) assumption, or a Partial-EU-DU model that combines the EU and the DU assumptions (Rolfe and Windle, 2015).

In Research Question 1, the utility functions of the Partial-EU1, Partial-EU2 and the Partial-EU-DU models are specified in Equation B.1, Equation B.2 and Equation B.3, respectively.

$$v_{ni} = \beta_{HR}^{imp}(H_{ni}^{imp} \times R_{ni}^{G}) + \beta_{HR}^{det}(H_{ni}^{det} \times R_{ni}^{L}) + \beta_{H}^{imp}H_{ni}^{imp} + \beta_{H}^{det}H_{ni}^{det} + \beta_V V_{ni} + \beta_C C_{ni} \quad \text{(B.1)}$$

$$v_{ni} = \beta_{HR}^{imp}(H_{ni}^{imp} \times R_{ni}^{G}) + \beta_{HR}^{det}(H_{ni}^{det} \times R_{ni}^{L}) + \beta_{R}^{G}R_{ni}^{G} + \beta_{R}^{L}R_{ni}^{L} + \beta_V V_{ni} + \beta_C C_{ni} \quad \text{(B.2)}$$

$$v_{ni} = \beta_{HR}^{imp}(H_{ni}^{imp} \times R_{ni}^{G}) + \beta_{HR}^{det}(H_{ni}^{det} \times R_{ni}^{L}) + \beta_{H}^{imp}H_{ni}^{imp} + \beta_{H}^{det}H_{ni}^{det} + \beta_{R}^{G}R_{ni}^{G} + \beta_{R}^{L}R_{ni}^{L} + \beta_V V_{ni} + \beta_C C_{ni} \quad \text{(B.3)}$$

where $\mathrm{H}_{\mathrm{ni}}^{\mathrm{imp}} \times \mathrm{R}_{\mathrm{ni}}^{\mathrm{G}}$ and $\mathrm{H}_{\mathrm{ni}}^{\mathrm{det}} \times \mathrm{R}_{\mathrm{ni}}^{\mathrm{L}}$ in Equation B.1 represent the interactions of the risk and health attributes in alternative *i* in the gain and loss domains, respectively. $\mathrm{H}_{\mathrm{ni}}^{\mathrm{imp}}$ and $\mathrm{H}_{\mathrm{ni}}^{\mathrm{det}}$ in Equation B.1 represent the additional independent health attribute in alternative *i* in the gain and loss domain, respectively, and the $\mathrm{R}_{\mathrm{ni}}^{\mathrm{G}}$ and $\mathrm{R}_{\mathrm{ni}}^{\mathrm{L}}$ in Equation B.2 represent the additional independent risk attribute in alternative *i* accordingly for the two domains.

It is expected that:

$\beta_{\mathrm{HR}}^{\mathrm{imp}} > 0, \beta_{\mathrm{HR}}^{\mathrm{det}} < 0; \beta_{\mathrm{H}}^{\mathrm{imp}} > 0, \beta_{\mathrm{H}}^{\mathrm{det}} < 0$ for the Partial-EU1 model (in Equation B.1)

$\beta_{\mathrm{HR}}^{\mathrm{imp}} > 0, \beta_{\mathrm{HR}}^{\mathrm{det}} < 0; \beta_{\mathrm{R}}^{\mathrm{G}} > 0, \beta_{\mathrm{R}}^{\mathrm{L}} > 0$ for the Partial-EU2 model (in Equation B.2)

$\beta_{\mathrm{HR}}^{\mathrm{imp}} > 0, \beta_{\mathrm{HR}}^{\mathrm{det}} < 0;\ \beta_{\mathrm{H}}^{\mathrm{imp}} > 0, \beta_{\mathrm{H}}^{\mathrm{det}} < 0;\ \beta_{\mathrm{R}}^{\mathrm{G}} > 0, \beta_{\mathrm{R}}^{\mathrm{L}} > 0$ for the Partial-EU-DU model (in Equation B.3)

Any parameter sign contradicting to the expectation implies that the estimated parameters for this utility specification is not consistent with its corresponding theoretical assumption.

Results from Table B.1 shows the means of random parameters in the Partial-EU2 specifications are conform to its corresponding theoretical assumptions. However, the interaction term ($\mathrm{H^{det}} \times \mathrm{R^{L}}$) in the Partial-EU1 specification (model 2) and the interaction term ($\mathrm{H^{imp}} \times \mathrm{R^{G}}$) in the Partial-EU-DU specification (model 4) imply inconsistency with the theoretical assumptions, as respondents should obtain utility when expected health outcomes improve and obtain disutility when expected health outcomes deteriorate. As for the statistical performance, the Partial-EU2 model has the smallest BIC value, and therefore has a better model fit compared to other models. However, the smaller BIC value of the DU model (DU, model 1) compared to the Partial-EU2 model suggesting that DU still has the best model fit.[62]

For the Research Question 2.1, the corresponding equations for the domain-asymmetric models according to the Partial-EU1, Partial-EU2 are presented in Equation B.4 and Equation B.5. Additionally, a domain-asymmetric model with prospect theory applied in the gain domain is also tested, which is presented in Equation B.6.

$$v_{ni} = \beta_{HR}^{imp}(H_{ni}^{imp} \times R_{ni}^{G}) + \beta_{H}^{imp}H_{ni}^{imp} + \beta_{H}^{det}H_{ni}^{det} + \beta_{R}^{L} * R_{ni}^{L} + \beta_{V}V_{ni} + \beta_{C}C_{ni} \quad \text{(B.4)}$$

$$v_{ni} = \beta_{HR}^{imp}(H_{ni}^{imp} \times R_{ni}^{G}) + \beta_{R}^{G} * R_{ni}^{G} + \beta_{H}^{det}H_{ni}^{det} + \beta_{R}^{L} * R_{ni}^{L} + \beta_{V}V_{ni} + \beta_{C}C_{ni} \quad \text{(B.5)}$$

$$v_{ni} = \beta_{HW}^{imp}[W^{+}(R_{ni}^{G}) \times H_{ni}^{imp}] + \beta_{H}^{det}H_{ni}^{det} + \beta_{R}^{L} * R_{ni}^{L} + \beta_{V}V_{ni} + \beta_{C}C_{ni} \quad \text{(B.6)}$$

Results in Table B.1 show that the coefficient of the $\mathrm{H^{imp}}$ is not significant in the Partial-EU1 (gain)-DU (loss) model (model 5), and thus the results for this model does not conform to its corresponding theoretical assumption. In terms of the model fit (measured by BIC values), the DU model (model 1) is better than the Partial-EU2 (gain)-DU(loss) (model 6) and the PT(Partial-EU2 (gain)-DU(loss) model (model 7), providing the evidence that DU behaviour is applied in both the gain and the loss domains.

[62] Using the J-test to compare these two non-nested models, results still suggest that the DU model fits the data better against the Partial EU2 model (the fitted-value term from the DU model has a significant impact (z-value=7.43) as a covariate in the Partial-EU2 model, whilst it is not the case for the opposite.

Table B.1 Results of mixed logit models for various partial expected utility specifications

Variables [a]	**(1) DU**	**(2) Partial-EU1**	**(3) Partial-EU2**	**(4) Partial-EU-DU**	**(5) Partial-EU1 (gain)-DU(loss)**	**(6) Partial-EU2 (gain)-DU(loss)**	**(7) PT(Partial-EU2 (gain))-DU(loss)**
Cost	-0.0004***	-0.0005***	-0.0001	-0.0004***	-0.0004***	-0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Random parameters (mean)							
ASC SQ	-2.712***	-1.382***	-2.574***	-4.422***	-1.833***	-2.439***	-2.505***
	(0.257)	(0.183)	(0.450)	(0.701)	(0.238)	(0.355)	(0.308)
Visibility	-0.125***	-0.135***	-0.096***	-0.145***	-0.132***	-0.124***	-0.132***
	(0.017)	(0.018)	(0.016)	(0.019)	(0.018)	(0.018)	(0.018)
$\mathrm{H^{imp}} \times \mathrm{R^G}$		0.007***	0.005**	-0.009**	0.007***	0.004**	
		(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	
$\mathrm{H^{imp}} * \mathrm{W^+}(\mathrm{R^G})$							1.299***
							(0.405)
$\mathrm{H^{det}} \times \mathrm{R^L}$		0.003**	-0.012***	-0.007**			
		(0.001)	(0.003)	(0.003)			
$\mathrm{H^{imp}}$	0.376***	0.080		0.780***	0.138		
	(0.105)	(0.106)		(0.186)	(0.106)		
$\mathrm{H^{det}}$	-0.920***	-1.314***		-0.515**	-1.232***	-1.132***	-1.126***
	(0.144)	(0.167)		(0.213)	(0.158)	(0.147)	(0.154)
$\mathrm{R^G}$	0.014***		0.014***	0.026***		0.008***	0.009***
	(0.002)		(0.003)	(0.005)		(0.003)	(0.002)
$\mathrm{R^L}$	0.007***		0.008**	0.017***	0.005***	0.006***	0.007***
	(0.002)		(0.003)	(0.005)	(0.002)	(0.002)	(0.002)
Standard deviations of parameters distribution							
ASC SQ	1.148***	1.912***	0.974***	1.032***	1.793***	1.016***	1.354***
	(0.201)	(0.157)	(0.292)	(0.248)	(0.176)	(0.237)	(0.264)
Visibility	0.221***	0.226***	0.195***	0.230***	0.221***	0.219***	0.222***
	(0.019)	(0.020)	(0.018)	(0.020)	(0.020)	(0.020)	(0.0195)
$\mathrm{H^{imp}} \times \mathrm{R^G}$		0.007***	0.010***	0.002	0.007***	0.008***	
		(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	
$\mathrm{H^{imp}} * \mathrm{W^+}(\mathrm{R^G})$							2.627***
							(0.378)
$\mathrm{H^{det}} \times \mathrm{R^L}$		0.008***	0.018***	0.007***			
		(0.002)	(0.002)	(0.002)			
$\mathrm{H^{imp}}$	1.013***	0.782***		0.976***	0.750***		
	(0.101)	(0.103)		(0.101)	(0.118)		
$\mathrm{H^{det}}$	1.580***	1.863***		1.610***	1.936***	1.680***	1.804***
	(0.138)	(0.146)		(0.149)	(0.153)	(0.162)	(0.153)
$\mathrm{R^G}$	0.020***		0.021***	0.020***		0.019***	0.017***
	(0.002)		(0.002)	(0.002)		(0.00)	(0.002)
$\mathrm{R^L}$	0.008***		0.009***	0.010***	0.009***	0.012***	0.010***
	(0.002)		(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Weighting function parameter							
Υ							0.350
Model statistics							
BIC	5957	6028	6178	5981	6028	6009	5981
McFadden R^2	0.159	0.151	0.135	0.160	0.152	0.154	0.157
n(observations) [c]	10,170	10,170	10,170	10,170	10,170	10,170	10,170

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; $\mathrm{H^{imp}}$ ($\mathrm{H^{det}}$) is the health attribute in the gain (loss) domain; $\mathrm{H^{imp}} \times \mathrm{R^G}$ ($\mathrm{H^{det}} \times \mathrm{R^L}$) is the interaction term between health and risk attributes in the gain (loss) domain; $\mathrm{H^{imp}} \times \mathrm{W}(\mathrm{R^G})$ is the interaction term between health and probability weighting function the gain domain; $\mathrm{R^G}$ ($\mathrm{R^L}$) is the risk attribute in the gain (loss) domain; Visibility is the visibility attribute; Cost is the cost attribute. (b) Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. (c) Number of observations is calculated according to the total number of choices times the number of alternatives instead of the conventional measure of the number of observations, due to the data structure of Stata.

Appendix B.2: Estimated probability weighting function

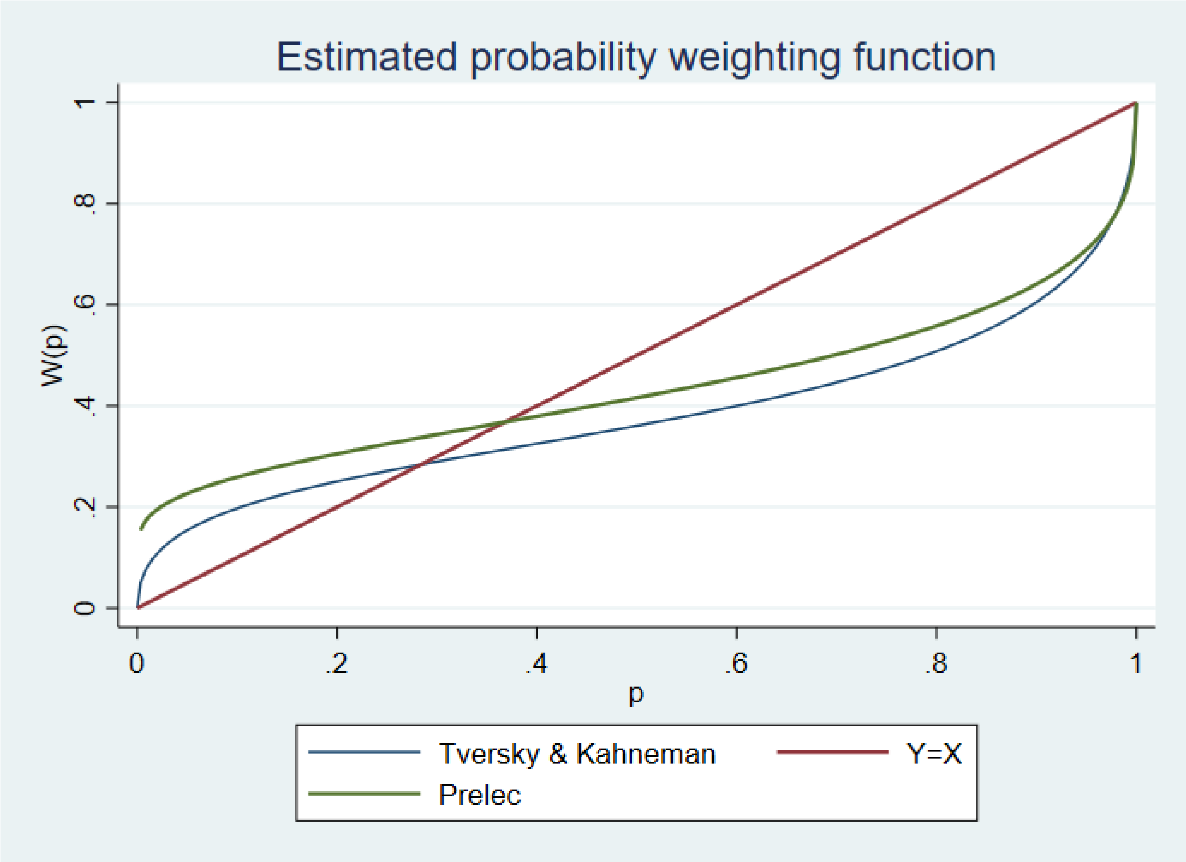


Figure B.1 Estimated probability weighting functions. Tversky & Kahneman is the Tversky and Kahneman (1992) weighting function applied to the PT model (model 4, Table 3.3); Prelec is the Prelec (1998) weighting function applied to the PT model (model 4, Table 3.3); Y=X is a baseline weighting function that assumes linear probability weighting.

Appendix C: Appendix for Chapter 4

Appendix C.1: The combined specification and domain-specific treatment specifications

I also compare the treatment-specific specification (model 1 in Table 4.3) with another two specifications in which the health attribute is treatment-specific either in the gain domain (model 1, Table C.1) or in the loss domain (model 2, Table C.1). Results from likelihood ratio tests suggest that the treatment-specific specification (model 1 in Table 4.3) has slightly better model fit than the specification only with treatment-specific health attribute in the gain domain or in the loss domain, but the improvement is insignificant.

Table C.1 Mixed logit model results for the combined specification and the treatment-specific specification in the gain or loss domain

	Treatment-specific model (gain) (model 1)		**Treatment-specific model (loss) (model 2)**		**Combined model (model 3)**	
Variables [a]	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Cost	-0.0003***	(0.0001)	-0.0003***	(0.0001)	-0.0003***	(0.0001)
λ (Scale parameter)	0.036	(0.094)	0.043	(0.098)	-0.021	(0.082)
Random parameters (mean)						
ASC SQ	-1.002***	(0.135)	-1.014 ***	(0.138)	-1.038***	(0.137)
H^{imp} (Combined)			0.578***	(0.079)	0.602***	(0.081)
H^{imp} (Certain)	0.545***	(0.100)				
H^{imp} (Uncertain)	0.620***	(0.111)				
H^{det} (Combined)	-0.812***	(0.111)			-0.848***	(0.113)
H^{det} (Certain)			-0.892***	(0.146)		
H^{det} (Uncertain)			-0.761***	(0.149)		
Visibility	-0.103***	(0.014)	-0.102***	(0.014)	-0.103***	(0.014)
Standard deviations of the random parameters						
ASC SQ	1.619***	(0.150)	1.594***	(0.138)	1.659***	(0.139)
H^{imp} (Combined)			0.858***	(0.091)	0.882***	(0.091)
H^{imp} (Certain)	1.062***	(0.112)				
H^{imp} (Uncertain)	0.560***	(0.139)				
H^{det} (Combined)	1.520***	(0.122)			1.566***	(0.118)
H^{det} (Certain)			1.654***	(0.148)		
H^{det} (Uncertain)			1.421***	(0.186)		
Visibility	0.155***	(0.017)	0.156***	(0.018)	0.158***	(0.017)
Model statistics						
AIC	7949		7955		7953	
BIC	8026		8032		8017	
Log-likelihood	-3962		-3966		-3967	
n(observations)	4,470		4,470		4,470	

Note: (a) ASC SQ is the alternative specific constant for the “current policies” option;H^{imp} (Certain)(H^{det} (Certain)) is the health attribute in the gain (loss) domain for the certain treatment, whilst H^{imp} (Uncertain) (H^{det} (Uncertain)) is the health attribute in the gain (loss) domain for the uncertain treatment; H^{imp} (Combined) (H^{det} (Combined)) is the health attribute in the gain (loss) domain without treatment-specific effects; Visibility is the visibility attribute; Cost is the cost attribute; (b) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix C.2: Treatment-specific specification with socio-economic interactions

Table C.2 Mixed logit model results: Treatment-specific specification with socio-economic interactions

	Main-effects		**Socio-economic Interactions** [b]							
			Gender		**Education**		**Income**		**No Deterioration**	
Variables [a]	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Cost	-0.0003***	(0.0001)								
λ (Scale parameter)	0.097	(0.116)								
Random parameters (mean)										
ASC SQ	-0.969***	(0.133)								
$\mathrm{H}^{\mathrm{imp}}$ (Certain)	0.552***	(0.101)								
$\mathrm{H}^{\mathrm{imp}}$ (Uncertain)	0.611***	(0.118)	-0.174**	(0.082)	-0.062	(0.077)	0.099	(0.080)	0.082	(0.079)
$\mathrm{H}^{\mathrm{det}}$ (Certain)	-0.910***	(0.148)								
$\mathrm{H}^{\mathrm{det}}$ (Uncertain)	-0.665***	(0.140)	-0.076	(0.114)	0.053	(0.049)	-0.184	(0.122)	-0.466***	(0.131)
Visibility	-0.098***	(0.014)								
Standard deviations of the random parameters										
ASC SQ	1.568***	(0.160)								
$\mathrm{H}^{\mathrm{imp}}$ (Certain)	1.036***	(0.113)								
$\mathrm{H}^{\mathrm{imp}}$ (Uncertain)	0.462***	(0.154)								
$\mathrm{H}^{\mathrm{det}}$ (Certain)	1.603***	(0.155)								
$\mathrm{H}^{\mathrm{det}}$ (Uncertain)	1.300***	(0.178)								
Visibility	0.151***	(0.017)								
Model statistics										
AIC	7903									
BIC	8045									
Log-likelihood	-3930									
n(observations)	4,470									

Note: (a) ASC SQ is the alternative specific constant for the 'current policies' option; $\mathrm{H}^{\mathrm{imp}}$ (Certain) ($\mathrm{H}^{\mathrm{det}}$ (Certain)) is the health attribute in the gain (loss) domain for the certain treatment, whilst $\mathrm{H}^{\mathrm{imp}}$ (Uncertain) ($\mathrm{H}^{\mathrm{det}}$ (Uncertain)) is the health attribute in the gain (loss) domain for the uncertain treatment; Visibility is the visibility attribute; Cost is the cost attribute; Gender is a the gender variable, with 2 representing female and 1 representing male; Education and Income are two categorical variables, with higher value representing higher education or income levels; No Deterioration is a dummy variable with value equalling to 1 if respondents claimed that they cannot accept the air quality to be deteriorated and value equalling to 0 if they can accept deteriorated air quality. (b) All the socio-economic variables are normalized to facilitate comparisons. (c) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix C.3: Random regret model

An alternative approach that can be used to interpret choice behaviour is random regret minimization (RRM) (Chorus, 2008), where individuals minimize anticipated regret in decision-making. In this chapter, I use a µRRM specification proposed by van Cranenburgh et al. (2015), in which the regret function represents the accumulated regrets from bilateral comparisons between alternatives (e.g., between alternative *i* and alternative *j*) in a choice set. The error term follows a Gumbel distribution. The regret function is specified by Equation C.1:

$$R_{ni} = \sum_{i \neq j} \sum_{m} \mu_m \ln \left[1 + e^{\frac{\beta_m (x_{im} - x_{im})}{\theta_m}} \right] + \varepsilon_{ni} \qquad \text{(C.1)}$$

where β_m captures the slope of the regret function for attribute *m* and the shape parameter μ_m captures the profundity of regret in choice comparisons. A large μ_m signals a small difference between regret minimization and utility maximization behaviour, and a small μ_m implies a strong degree of regret. The µRRM model is used to test whether the RRM is a more appropriate behavioural assumption over RUM. The estimations of RRM are run using the Apollo package (Hess and Palma, 2019).

Table C.3 Results of random regret minimization model for the treatment-specific specification

Variables [a]	Coefficient	S.E.
Cost	-0.0001	(0.0001)
λ (Scale parameter)	-0.425	(0.278)
ASC SQ	-0.026*	(0.016)
H^{imp} (Certain)	0.300***	(0.037)
H^{imp} (Uncertain)	0.567***	(0.173)
H^{det} (Certain)	-0.209***	(0.040)
H^{det} (Uncertain)	-0.117***	(0.048)
Visibility	-0.049***	(0.007)
u	8.444*	(4.921)

Table C.3 Continued

Model statistics	
AIC	9270
BIC	9327
Log-likelihood	-4626
n(observations)	4,470

Note: (a) Cost is the cost attribute; ASC SQ is the alternative specific constant for the "current policies" option; $\mathrm{H}^{\mathrm{imp}}$ (Certain) ($\mathrm{H}^{\mathrm{det}}$ (Certain)) is the health attribute in the gain (loss) domain for the certain treatment, whilst $\mathrm{H}^{\mathrm{imp}}$ (Uncertain) ($\mathrm{H}^{\mathrm{det}}$ (Uncertain)) is the health attribute in the gain (loss) domain for the uncertain treatment; Visibility is the visibility attribute; u captures the degree of regret. (b) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix D: Appendix for Chapter 5

Appendix D.1: Taboo trade-off aversion and attribute non-attendance for Treatment 2 and 3

Table D.1 Results of mixed logit model with taboo trade-off aversion incorporated (Treatment 2)

	MXL		**Both taboos**		**Attribute-specific taboo (Health)**		**Attribute-specific taboo (Visibility)**	
Variables [a]	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
ASC SQ	-2.980***	1.186***	-3.097***	-1.271***	-3.179***	1.262***	-3.033***	-1.093***
	(0.267)	(0.233)	(0.272)	(0.186)	(0.277)	(0.167)	(0.271)	(0.261)
H^{imp}	0.467***	0.935***	0.460***	1.029***	0.457***	-0.988***	0.520***	0.981***
	(0.104)	(0.109)	(0.107)	(0.115)	(0.106)	(0.106)	(0.108)	(0.109)
H^{det}	-0.972***	1.570***	-0.776***	1.495***	-0.705***	1.405***	-0.870***	1.427***
	(0.149)	(0.149)	(0.143)	(0.135)	(0.146)	(0.160)	(0.146)	(0.135)
Visibility	-0.128***	0.226***	-0.103***	0.223***	-0.130***	0.225***	-0.095***	0.216***
	(0.018)	(0.020)	(0.022)	(0.021)	(0.018)	(0.021)	(0.022)	(0.022)
C^{inc}	-0.0010***		-0.0014***		-0.0016***		-0.0017***	
	(0.0002)		(0.0002)		(0.0002)		(0.0003)	
C^{dec}	-0.0006**		-0.0006***		-0.0003		-0.0004	
	(0.0002)		(0.0002)		(0.0003)		(0.0002)	
R^G	0.014***	0.020***	0.013***	0.020***	0.015***	0.019***	0.014***	0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R^L	0.008***	0.011***	0.008***	0.009***	0.010***	0.010***	0.008***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Taboo Penalty			-0.302*	-0.439	-0.859***	2.070***	-0.382***	0.917***
			(0.155)	(0.348)	(0.218)	(0.226)	(0.140)	(0.165)
Model statistics								
Log-likelihood	-2905		-2904		-2873		-2893	
BIC	5939		5956		5894		5934	

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; H^{imp} (H^{det}) is the health attribute in the gain (loss) domain; Visibility is the visibility attribute; C^{inc} (C^{dec}) is the cost attribute when the bill is specified as increase (decrease); Taboo Penalty is the taboo term capturing preference of taboo trade-off aversion, the definition of which varies in different taboo specifications. (b) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table D.2 Results of mixed logit model with taboo trade-off aversion incorporated (Treatment 3)

	MXL		**Both taboos**		**Attribute-specific taboo (Health)**		**Attribute-specific taboo (Visibility)**	
Variables [a]	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
ASC SQ	-1.266***	-1.883***	-1.163***	-1.888***	-1.466***	-1.961***	-1.144***	-1.917***
	(0.236)	(0.187)	(0.245)	(0.187)	(0.251)	(0.194)	(0.249)	(0.196)
$\mathrm{H}^{\mathrm{imp}}$	0.660***	0.583***	0.726***	0.544***	0.588***	-0.549***	0.716***	0.607***
	(0.117)	(0.142)	(0.132)	(0.164)	(0.122)	(0.160)	(0.125)	(0.161)
$\mathrm{H}^{\mathrm{det}}$	-0.700***	1.496***	-0.655***	1.503***	-0.625***	1.448***	-0.672***	1.499***
	(0.164)	(0.143)	(0.163)	(0.142)	(0.175)	(0.157)	(0.165)	(0.143)
Visibility	-0.096***	0.150***	-0.102***	0.136***	-0.096***	0.153***	-0.115***	0.132***
	(0.020)	(0.023)	(0.023)	(0.028)	(0.021)	(0.024)	(0.024)	(0.027)
$\mathrm{C}^{\mathrm{inc}}$	-0.0007***		-0.0007***		-0.0010***		-0.0006**	
	(0.0002)		(0.0002)		(0.0003)		(0.0003)	
$\mathrm{C}^{\mathrm{dec}}$	-0.0004*		-0.0005*		-0.0002		-0.0006**	
	(0.0003)		(0.0003)		(0.0003)		(0.0003)	
Taboo Penalty			-0.012	-0.979***	-0.540***	-1.023***	0.174	-0.707***
			(0.191)	(0.240)	(0.174)	(0.203)	(0.163)	(0.172)
Model statistics								
Log-likelihood	-1931		-1927		-1921		-1928	
BIC	3951		3960		3947		3961	

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; $\mathrm{H}^{\mathrm{imp}}$ ($\mathrm{H}^{\mathrm{det}}$) is the health attribute in the gain (loss) domain; Vsibility is the visibility attribute; $\mathrm{C}^{\mathrm{inc}}$ ($\mathrm{C}^{\mathrm{dec}}$) is the cost attribute when the bill is specified as increase (decrease); Taboo Penalty is the taboo term capturing preference of taboo trade-off aversion, the definition of which varies in different taboo specifications. (b) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table D.3 Main estimation results of cost attribute non-attendance (Treatment 2)

	MNL	ECLC (cost decrease)	ECLC-MXL (cost decrease)	
Variables [a]			Mean	S.D.
ASC SQ	-0.332***	-0.527***	-1.652***	-2.050***
	(0.106)	(0.105)	(0.194)	(0.187)
H^{imp}	0.533***	0.520***	0.572***	0.826***
	(0.066)	(0.068)	(0.103)	(0.132)
H^{det}	-0.324***	-0.260***	-0.950***	1.723***
	(0.068)	(0.070)	(0.147)	(0.148)
Visibility	-0.078***	-0.078***	-0.135***	0.231***
	(0.009)	(0.009)	(0.019)	(0.021)
C^{inc}	-0.0010***	-0.0014***	-0.0021***	-0.0027***
	(0.0002)	(0.0002)	(0.0003)	(0.0004)
C^{dec}	-0.0006***			
	(0.0002)			
Classes and probabilities				
Class 1 (Cost ANA) [b]		0	0	
Class 2		-0.029***	-0.045***	0.035***
		(0.004)	(0.009)	(0.005)
π^1		0.805*** [c]	0.804***	
		(0.023)	(0.028)	
π^2		0.195***	0.196***	
		(0.023)	(0.028)	
Model statistics				
Log-likelihood	-3497	-3329	-2876	
BIC	7043	6714	5858	

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; H^{imp} (H^{det}) is the health attribute in the gain (loss) domain; Visibility is the visibility attribute; C^{inc} (C^{dec}) is the cost attribute when the bill is specified as increase (decrease); (b) Respondents are segmented to two classes for the ECLC and ECLC-MXL models. Class 1 (Cost ANA) is the coefficient for the cost ANA class, with its corresponding class probability being π^1; Class 2 is the coefficient for the attended cost class, and the probability of class attendance is π^2. (c) The standard errors of the class probabilities are calculated using the Delta method. (d) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table D.4 Main estimation results of cost attribute non-attendance (Treatment 3)

	MNL	**ECLC (cost decrease)**	**ECLC- MXL (cost decrease)**	
Variables [a]			Mean	S.D.
ASC SQ	-0.128	-0.211	-1.326***	-1.723***
	(0.143)	(0.144)	(0.250)	(0.209)
H^{imp}	0.635***	0.694***	0.729***	0.633***
	(0.085)	(0.090)	(0.132)	(0.148)
H^{det}	-0.033	-0.025	-0.856***	-1.711***
	(0.082)	(0.085)	(0.184)	(0.159)
Visibility	-0.047***	-0.045***	-0.107***	0.181***
	(0.013)	(0.013)	(0.022)	(0.027)
C^{inc}	-0.0004*	-0.0006***	-0.0008**	-0.0028***
	(0.0002)	(0.0002)	(0.0004)	(0.0005)
C^{dec}	-0.0005**			
	(0.0002)			
Model statistics				
Class 1 (Cost ANA)[b]		0	0	
Class 2		0.009	-0.006***	0.000
		(0.006)	(0.002)	(0.003)
Class 3		-0.008***	0.003	0.024***
		(0.001)	(0.005)	(0.009)
π^1		0.767***[c]	0.731***	
		(0.045)	(0.094)	
π^2		0.036	0.200**	
		(0.028)	(0.087)	
π^3		0.197***	0.069***	
		(0.035)	(0.026)	
Model statistics				
Log-likelihood	-2276	-2220	-1892	
BIC	4598	4510	3906	

Note: (a) ASC SQ is the alternative specific constant for the "current policies" option; H^{imp} (H^{det}) is the health attribute in the gain (loss) domain, Visibility is the visibility attribute; C^{inc} (C^{dec}) is the cost attribute when the bill is specified as increase (decrease); (b) Respondents are segmented to three classes for the ECLC and ECLC-MXL models. Class 1 (Cost ANA) is the coefficient for the cost ANA class, with its corresponding class probability being π^1; Class 2 and 3 are the coefficients for the attended cost classes, and the probability of class attendance are $\pi^2$and π^3, respectively. (c) The standard errors of the class probabilities are calculated using the Delta method. (d) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix D.2: Mixed logit model results with individual-level explanatory variables

Table D.5 Results of mixed logit model with interactions between the cost decrease variable and various individual characteristics & attitudinal variables

	Treatment 1		Treatment 2		Treatment 3	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Interactions [a]						
Age	0.000		0.001*		0.001***	
	(0.000)		(0.000)		(0.000)	
Income	-0.000		-0.000		-0.000	
	(0.000)		(0.000)		(0.000)	
Gender	0.000		-0.001		0.000	
	(0.001)		(0.000)		(0.000)	
Education	0.002**		-0.001		0.002***	
	(0.001)		(0.001)		(0.001)	
Not accepting air deterioration	-0.002***		-0.001**		-0.001	
	(0.001)		(0.000)		(0.001)	
Ignore cost	-0.001		-0.001*		0.002**	
	(0.001)		(0.001)		(0.001)	
Survey difficulty	-0.000		0.000		-0.000*	
	(0.000)		(0.000)		(0.000)	
Responsible for bill	-0.001		0.001*		0.002**	
	(0.001)		(0.001)		(0.001)	
Attribute parameters [b]						
C^{inc}	-0.0015***		-0.0014***		-0.0007***	
	(0.0003)		(0.0002)		(0.0002)	
C^{dec}	-0.0025		0.0009		-0.0096***	
	(0.0026)		(0.0024)		(0.0024)	
ASC SQ	-1.178***	1.440***	-3.047***	-1.140***	-1.187***	-1.804***
	(0.166)	(0.163)	(0.266)	(0.282)	(0.264)	(0.215)
H^{imp}	0.576***	1.076***	0.454***	1.070***	0.721***	-0.690***
	(0.109)	(0.117)	(0.108)	(0.106)	(0.124)	(0.134)
H^{det}	-0.861***	1.571***	-0.864***	1.451***	-0.717***	1.495***
	(0.144)	(0.144)	(0.142)	(0.157)	(0.164)	(0.141)

Table D.5 Continued

Visibility	-0.110***	0.177***	-0.126***	0.229***	0.099**	-0.161***
	(0.020)	(0.023)	(0.018)	(0.021)	(0.042)	(0.062)
R^{G}			0.014***	-0.020***		
			(0.002)	(0.002)		
R^{L}			0.008***	0.008**		
			(0.002)	(0.003)		
Model statistics						
Log-likelihood	-2000		-2889		-1912	
BIC	4158		5980		4001	

Note: (a) Age is the averaged midpoints of the ranges of respondents' age (in year); Income is a categorical variable that represents the midpoints of ranges of respondents' annual income (in RMB); Gender is the gender dummy variable taking the value 1 if the respondent is male and 0 if female. Education is respondents' highest education level; Not accept air deterioration is the self-reported unacceptance of air quality deterioration scenarios (equals 1 if reported deterioration scenario is unacceptable, and 0 if acceptable); Ignore cost is the self-reported ignoring of the cost attribute (equals 1 if a respondent stated to have ignored the cost attribute, and 0 if not); Survey difficulty is the self-reported difficulty of the experiment scaled from 1 (very easy) to 5 (very hard); Responsible for bill is the self-reported responsibility for the household bill (Yes/No). (b) ASC SQ is the alternative specific constant for the "current policies" option; H^{imp} (H^{det}) is the health attribute in the gain (loss) domain; Visibility is the visibility attribute; C^{inc} (C^{dec}) is the cost attribute when the bill is specified as increase (decrease). (c) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix D.3: Questionnaire pre-tests and pilot data collection

Although DCE is a quantitative approach, the use of qualitative approaches is recommended in the development of context description and attributes, which contributes to the external validity of the DCE (Coast et al, 2012; Kløjgaard et al., 2012).

1. Pre-test processes

Questionnaire pre-tests were conducted during April and May 2018 at the University of Southampton, U.K., to collect feedback from respondents on their understanding of the context and policy scenarios of the questionnaire.

A convenient sampling method was used to select Chinese students[63] from the University of Southampton in order to conduct the pre-tests. Focus groups and face-to-face interviews were conducted during the pre-test, and both the qualitative methods are popular in DCE literature (Kløjgaard et al, 2012). After signing the participation form, respondents were firstly asked to complete the questionnaire on their phones. After that, they were asked to participate in either a focus group discussion or a personal interview. In the focus group, participants were asked to sit around a table and gave opinions about the questionnaire they had completed. The principle investigator then led the discussion based on their comments. In the face-to-face interviews, each respondent was invited to join in a conversation in a public and comfortable space (e.g., coffee shop). The principle investigator asked a series of questions regarding their personal experiences about air pollution, as well as the hypothetical scenarios and attributes of the DCE. On average, it took 1.5 hours to complete the focus group and an hour to complete an interview.

26 participants joined in the pre-tests (including all versions of the survey). Six participants attended the focus group and 20 students participated in the face-to-face interviews. All participants were students of University of Southampton; six of them were undergraduates and 20 were postgraduates. There were five participants coming from courses related to economics, however, no evidence shows that these participants had a better understanding of the topic or methods related to this study than any of the other students.

[63] I use the convenient sampling instead of a more sophisticated sampling method, as the pre-tests cannot be conducted in Beijing (where the targeted population is located) due to financial constraints. Organizing focus groups and interviews in Beijing would cost 30-50 RMB per respondent, according a marketing company that was contacted in Beijing, and the researcher cannot afford this price. Therefore, convenient sampling method is the most reasonable method to be used for the pre-tests given the limited budget.

Of those who completed the pre-tests, only two participants were from Beijing, which is the study area. In order to collect more opinions from the targeted population, additional ten online questionnaires were used to collect feedback from people who were working in Beijing. The results are reported below.

2. Pre-test results

Some main issues were found and reported at the initial stage of the pre-test:

(1) Attributes

Participants thought that the attributes listed in the questionnaire were consistent with their perceptions about the effects of air pollution. However, firstly, they thought that health and visibility attributes were highly correlated, and thus an increase in health and a decrease in visibility could not be achieved within the same policy. Secondly, the concept of “Low visibility days” was confusing. Thirdly, some respondents mentioned that they did not want to “trade-off life with money”, showing a non-compensatory behaviour.

(2) Levels

Participants generally thought that the attribute levels for health and visibility were reasonable. However, the range of the cost attribute was too small.

Several changes were made given these feedback. First, scientific explanations about the possibility of separated health and visibility effects were provided to update each respondent’s understanding about air pollutants and anti-pollution implementation. This was to ensure that they would not be confused if a policy proposed a health and a visibility effect with opposite directions. Second, the cost range was repeatedly enlarged until respondents thought that it was large enough to be accounted for. Third, “Low visibility days” were replaced with “Bad visibility days”, and a pair of photos were added to assist respondents visually comparing the “bad” and the “good” visibility days. Fourth, for the health attribute, mortality due to air pollution was replaced with hospital admission, which was supposed to make the situation less serious and allow respondents to consider other attributes in decision making (i.e., respondents would ignore other attributes and only focus on the health attribute, if the description of the health effect was too pressing). Feedback from subsequent rounds of interviews confirmed that the issues mentioned above were solved (or at least mitigated).

As only two respondents from Beijing were interviewed in face-to-face interviews, ten supplementary questionnaires were sent to respondents who were working in Beijing through an online survey system, to collect more feedback. Results from these questionnaires showed that respondents perceived that the current levels of the health and visibility attributes were appropriate. In addition, most of them stated that the payment vehicle was realistic. The self-reported household electricity, gas and heating bills from these participants were on average 210-390 RMB/month, which supported the appropriateness of the range of the cost attribute.

3. Pilot data collection

Pilot data were collected with 20 respondents per treatment during June and July, 2018 through an online system.[64]

[64] Due to the anonymity request from the marketing company, their name is only available upon request.

Appendix D.4 Questionnaires used in this thesis (the discrete choice experiments part)

Appendix D.4.1 English version

Treatment 1 (Chapter 2)

Part 1

You will be given an introduction about air pollution in China and answer questions about how air pollution affects you and people around you

Introduction

In recent years, air pollution has become a commonly discussed issue in China. According to data from the World Health Organisation and the World Bank, over a million people in China die each year due to air pollution. The loss due to air pollution in China in 2013 was equal to 9.92% of its Gross domestic product.

There are mainly two ways in which air pollution may affect the wellbeing of people in your area:

(1) Health effect

Many substances in polluted air damage people's health, particularly the invisible small particles (e.g., PM10 and PM2.5). Inhaling these particles increases the likelihood of heart and lung diseases. Scientists have shown that air pollution is one of the most important factors that contributes to lung cancer, stroke and cardiovascular diseases. According to the Greenpeace, about 1.6 million people died in China because of diseases triggered by air pollution in 2013. In addition, air pollution in China also causes 6.8 million hospital admissions each year.

(2) Visibility effect

Severe air pollution may also cause poor visibility, and thus slow down the traffic in rush hour, delay air flights and lead to more traffic accidents in your city. Additionally, poor visibility hinders emergency and rescue operations in your city.

Now, we would like to ask you some questions about your experience of the air pollution effects.

Question 1: How often do you hear people around you talking about the health and visibility effects of air pollution in China?

A: Often
B: Sometimes
C: Never
D: I don't know

Question 2: How likely do you think it is that your health or that of your family will be affected by air pollution?

A: Very likely
B: Somewhat likely
C: Somewhat unlikely
D: Very unlikely

Question 3: Do you think you know enough about air pollution (for example, air pollutants, effects of air pollution and pollution-related policies) through social media or people around you ?

A: I know quite a lot
B: I have some knowledge about it
C: I know little about it

Question 4: Have you ever changed any of your daily activities to contribute to the reduction of air pollution? For example, have you tried to take public transport instead of driving your own car? or tried to use clean energy for home energy use?

A: Often
B: Sometimes
C: Never
D: I don't know

Part 2

Please read the introduction and answer the questions about your opinion on air pollution. Please read the following text patiently as it helps you to better understand the context and express your opinions.

There are many sources of air pollution. In order to tackle this issue in Beijing, the local government has implemented relevant policies in recent years. The key actions include shutting down polluting factories that did not reach the environmental standards set by the central government, applying new technologies to the polluting industries, and developing renewable energy, such as wind, water and solar power.

Following the Air Pollution Prevention and Control Action Plan published by the State Council of China, there are some achievements on air quality management. Data from the local environmental protection bureau shows that in the last 5 years in Beijing, the level of air pollution has been reduced by one third, which meets the target set by the central government.

Now, a decision on air pollution actions need to be made for the next five years.

- What is the current situation?

If the implementation level remains unchanged as of now, the current budget of the local government will be spent on actions to ensure that the number of hospital admissions due to air pollution in Beijing will remain at **130,000** per year, and the number of low visibility days will remain at **eight** days per month.

- What governmental actions will be taken in the future?

The actions mainly focus on the health and visibility effects of air pollution. The government may take different types of actions to deal with these two different air pollution effects. Some actions can deal with the visibility effects and some other actions can deal with the health effects, **so it is possible to have actions that alleviate health problems but aggravate visibility problems, or the other way around.**

- When will the new policy outcomes be achieved?

The policy outcomes are expected to be achieved by the end of 2022

- Why should I pay or get compensation?

Now, we would like to know your preference on the actions and objectives for air pollution reduction. If you would like to see the situation improve in any of the effects, then you may need to **pay extra** to fund the additional activities needed. If you would be satisfied with lower health or visibility levels, then you may **receive some of your money** back, as fewer of the planned actions would have to be undertaken.

- **A bit of scientific knowledge**

Why the effects of health and visibility are separable?

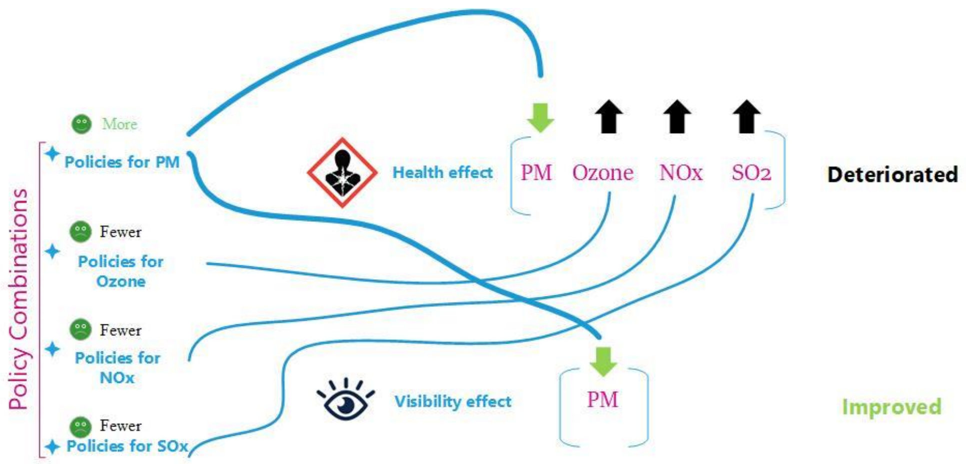
Scientists have proved that the health and visibility effects of air pollution are not necessarily related, because they have different sources. According to the reports from the United Nations and the Environmental Protection Agency of the United States, people's health is affected by detrimental substances like ozone, nitrogen oxide (NOx), particulate matter (PM) and sulphur dioxide (SO2), but visibility is mainly affected by particulate matter.

- Health: Ozone, NOx, PM, SO2
- Visibility: PM

In our context, government will implement a combination of policies to alleviate air pollution problems, and due to the limited governmental budget, a policy combination cannot target all air pollutants at the same time.

The picture (figure 1) below provides a visual example.

In the example, after implementing a policy combination, visibility issue will be alleviated while health will be aggravated, if the government implements **more** policies (compared with the current level of actions) to reduce PM, and **fewer** policies to reduce other detrimental substances, in other words, ozone, NOx and SO2. Accordingly, you need to pay extra money for the improved visibility, but will receive some of your money back due to the deteriorated health issue.



Note

PM=Particulate Matter (Including PM2.5, PM10)

NOx= Nitrogen Oxide

SO2= Sulphur Dioxide

Figure 1: Visibility is alleviated while Health is aggravated

If more policies for PM, and fewer policies for Ozone, NOx, and SO2, Visibility will be improved, but Health will be deteriorated.

Similarly, visibility could be aggravated, but the health issue is alleviated, if the government implements more policies to reduce ozone, NOx and SO2, and fewer policies to reduce PM. Accordingly, you need to pay extra money for the improved health, but will receive some of your money back due to the deteriorated visibility issue.

[Question]: Now, do you understand that it is possible to have actions that **alleviate the health problem** but **aggravate the visibility problem** or the other way around?

- Yes, I understand
- No, I don't understand, and would like to read the instruction again

- How is the payment change achieved?

This payment change will be achieved through an increase or decrease in your monthly household electricity, gas and heating bill. The change in your bill will be organised by state owned electric power and gas companies (for example, State Grid Corporation of China and China Gas), and they will cooperate with the local government to achieve clean air plans.

[Please read the following text patiently as it helps you to better understand the context and express your opinions.]

In order to assist the government in making policies to tackle the air pollution issue, they need to hear your voice as a citizen in your city.

The tables below show the potential air pollution effects on people, after the governmental actions are implemented.

Three different characteristics are listed: health, visibility, and payment effects. Note that these effects have a range of possible levels.

Health effects: The effect of air pollution on health in your local area. This is represented by the number of hospital admissions per year due to air pollution. The man shape icon represents 100 thousand people who go to hospital due to air pollution related diseases in your area. 

Health (number of hospital admissions per year)

150,000 hospital admissions per year

(**20,000** or **15% more**)

145,000 hospital admissions per year

(**15,000 or 11% more**)

140,000 hospital admissions per year

(**10,000 or 7.5% more**)

130,000 hospital admissions per year

(no change)

Current situation

120,000 hospital admissions per year

(**10,000 or 7.5% less**)

115,000 hospital admissions per year

(**15,000 or 11% less**)

110,000 hospital admissions per year

(**20,000** or **15% less**)

Visibility effects: The number of bad visibility days per month in your local area. On a bad visibility day, visibility on traffic roads is less than 1.5 kilometres. The picture below compares a bad visibility day (left) to a good visibility day (right).

Bad visibility ***Good visibility***

Visibility (number of bad visibility days per month)

Visibility (number of bad visibility days per month)	
12 days of bad visibility per month (**4** days more)	
10 days of bad visibility per month (**2** days more)	
8 days of bad visibility per month (no change)	**Current situation**
6 days of bad visibility per month (**2** days less)	
4 days of bad visibility per month (**4** days less)	

Electricity, gas and heating bill: Your choices of different policies are accompanied by changes in your household monthly electricity, gas and heating bill. Your monthly bill will remain unchanged if you choose to maintain the current set of actions.

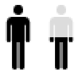
Electricity, gas and heating bill change per household per month (year)	
500 RMB increase/month （**6000** RMB increase/year） 	
200 RMB increase/month （**2400** RMB increase/year ） 	
100 RMB increase/month （**1200** RMB increase/year ） 	
No change in bill	**Current situation**
100 RMB decrease/month （**1200** RMB decrease/year ） 	
300 RMB decrease/month （**3600** RMB decrease/year ） 	
500 RMB decrease/month （**6000** RMB decrease/year ） 	

Note that if the amount of bill decrease exceeds your monthly electricity, gas and heating bill, it means that you don't need to pay any bills and the exceeding amount will be transferred to your bank account.

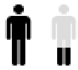
[Please read the following text patiently as it helps you to better understand the context and express your opinions.]

Now, we will show you three different policies. We want to know which of these policies you prefer the most.

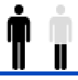
***Policy A**:* If you choose this option, the number of hospital admissions in your city due to air pollution will be [150 thousand per year (20 thousand more (or 15% more) than the situation under the current implementation)]. Additionally, you accept 12 days of bad visibility per month instead of 8 days under the current implementation. Your monthly household electricity, gas and heating bill will reduce by 500 RMB (or 6,000 RMB annual reduction) for accepting this policy.

Attributes	**Policy A**
Health (hospital admissions/year)	**150** thousand hospital admissions per year (**20** thousand more or **15%** more) 
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)
Cost per household per month (change in electricity, gas and heating bill)	**500** RMB per month bill decrease （**6000** RMB per year bill decrease） 

Policy B: If you choose this option, the number of hospital admissions in your city due to air pollution will be [120 thousand per year (10 thousand less (or 7.5% less) than the situation under the current implementation)]. Additionally, you accept 10 days of bad visibility per month instead of 8 days under the current implementation. Your monthly household electricity, gas and heating bill will increase by 100 RMB (or 1,200 RMB annual increase) for this policy.

Attributes	**Policy B**
Health (hospital admissions/year)	**120** thousand hospital admissions per year (**10** thousand less or **7.5%** less) 
Visibility (number of bad visibility days per month)	**10** days of bad visibility per month (**2** days more)
Cost per household per month (change in electricity, gas and heating bill)	**100** RMB per month bill increase （**1200** RMB per year bill increase ） 

It is possible that you find the two policies not suitable for you, because you do not think you will benefit from them compared to the current set of actions. In that case, you may choose the **current policies**. This option would mean that you want to keep things as they are now.

Attributes	**Current policies**
Health (hospital admissions/year)	**130** thousand hospital admissions per year (no change) 
Visibility (number of bad visibility days per month)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	No change in bill

Please be assured that there are no correct choices, we just want your opinions. Note that you may prefer other options not mentioned here to deal with air quality in your area.

Now, to understand how it works, let's do a warm-up question. Please choose the option that you prefer the most.

	Policy A	**Policy B**	**Current policies**
Health (hospital admissions/year)	**150** thousand per year (**20** thousand more or **15%** more) 	**120** thousand per year (**10** thousand less or **7.5%** less) 	**130** thousand per year (no change) 
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)	**10** days of bad visibility per month (**2** days more)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	**500** RMB per month bill decrease （**6,000** RMB per year bill decrease ） 	**100** RMB per month bill increase （**1,200** RMB per year bill increase ） 	No change in bill

In the following questions, please select your most preferred policy among the three policies (Policy A, Policy B and Current policies) shown in each choice card. There are 10 questions like this. Each choice is a new situation, so please consider each new choice as independent from the previous choice you made.

Remember that although there may be someone else in your family who pays the bill for you, you need to make decisions as if you contribute to the payment too.

Keep in mind that if you decide to pay the extra money stated in the project you choose, the amount of money you may spend on other health and environmental programmes, and on the everyday products you buy, will be reduced. On the other hand, if you decide to accept the monetary compensation stated in the project you choose, the amount of money you may spend on other health and environmental programmes, and on the everyday products you buy, will be increased.

(PAGE BREAK HERE)

Choice Card 1

Choice Card 2

…

Choice Card 10

Now we would like you to know more about the choices you have just made.

1. Please indicate why you choose the *current policies* option? **(multiple answers allowed)**

   A: My income is too low, so I cannot afford to pay more

   B: I think air pollution is not an important issue in my area, so there is no need to pay

   C: I don't think that the policy will be effective enough to change the air quality

   D: I don't want the air quality to be deteriorated

   E: I believe that citizens should not pay more for better air quality

   F: other reasons, please specify: _______

2. When making your choices, did you find a deterioration of health and/or visibility ever acceptable?
   A: Yes
   B: No

2.1. If no, please indicate why you think so?

   A: I don't want to sacrifice the environment, even if my gas, electricity and heating bill is reduced

   B: other reasons, please specify: _______

3. Do you think that the choices you just made were difficult or easy?

("1" is very easy; "2" is a bit easy; "3" is normal; "4" is a bit difficult; "5" is very difficult)

4. Did you find yourself ignoring any elements when making choices? **(multiple answers allowed)**

   A: I ignored the element "Health"

   B: I ignored the element "Visibility"

   C: I ignored the element "Electricity, gas and heating bill"

   D: I considered all three elements **(exclusive)**

4.1. If you found yourself making choices only based on one or two elements, Why was this? **(multiple answers allowed)**

   A: There were too many elements that need to be considered in decision making

   B: I did not consider some elements because I don't believe they can be achieved

   C: I did not consider some elements because I don't think they are important to me

   D: Other reason, please specify______

Treatment 2 (Chapter 3)

Part 1

You will be given an introduction about air pollution in China and answer questions about how air pollution affects you and people around you

Introduction

In recent years, air pollution has become a commonly discussed issue in China. According to data from the World Health Organisation and the World Bank, over a million people in China die each year due to air pollution. The loss due to air pollution in China in 2013 was equal to 9.92% of its Gross domestic product.

There are mainly two ways in which air pollution may affect the wellbeing of people in your area:

(3) Health effect

Many substances in polluted air damage people's health, particularly the invisible small particles (e.g., PM10 and PM2.5). Inhaling these particles increases the likelihood of heart and lung diseases. Scientists have shown that air pollution is one of the most important factors that contributes to lung cancer, stroke and cardiovascular diseases. According to the Greenpeace, about 1.6 million people died in China because of diseases triggered by air pollution in 2013. In addition, air pollution in China also causes 6.8 million hospital admissions each year.

(4) Visibility effect

Severe air pollution may also cause poor visibility, and thus slow down the traffic in rush hour, delay air flights and lead to more traffic accidents in your city. Additionally, poor visibility hinders emergency and rescue operations in your city.

Now, we would like to ask you some questions about your experience of the air pollution effects.

Question 1: How often do you hear people around you talking about the health and visibility effects of air pollution in China?

A: Often
B: Sometimes
C: Never
D: I don't know

Question 2: How likely do you think it is that your health or that of your family will be affected by air pollution?

A: Very likely
B: Somewhat likely
C: Somewhat unlikely
D: Very unlikely

Question 3: Do you think you know enough about air pollution (for example, air pollutants, effects of air pollution and pollution-related policies) through social media or people around you ?

A: I know quite a lot
B: I have some knowledge about it
C: I know little about it

Question 4: Have you ever changed any of your daily activities to contribute to the reduction of air pollution? For example, have you tried to take public transport instead of driving your own car? or tried to use clean energy for home energy use?

A: Often
B: Sometimes
C: Never
D: I don't know

Part 2

Please read the introduction and answer the questions about your opinion on air pollution. Please read the following text patiently as it helps you to better understand the context and express your opinions.

There are many sources of air pollution. In order to tackle this issue in Beijing, the local government has implemented relevant policies in recent years. The key actions include shutting down polluting factories that did not reach the environmental standards set by the central government, applying new technologies to the polluting industries, and developing renewable energy, such as wind, water and solar power.

Following the Air Pollution Prevention and Control Action Plan published by the State Council of China, there are some achievements on air quality management. Data from the local environmental protection bureau shows that in the last 5 years in Beijing, the level of air pollution has been reduced by one third, which meets the target set by the central government.

Now, a decision on air pollution actions need to be made for the next five years.

- What is the current situation?

If the implementation level remains unchanged as of now, the current budget of the local government will be spent on actions to ensure that the number of hospital admissions due to air pollution in Beijing will remain at **130,000** per year, and the number of low visibility days will remain at **eight** days per month.

- What governmental actions will be taken in the future?

The actions mainly focus on the health and visibility effects of air pollution. The government may take different types of actions to deal with these two different air pollution effects. Some actions can deal with the visibility effects and some other actions can deal with the health effects, **so it is possible to have actions that alleviate health problems but aggravate visibility problems, or the other way around.**

- When will the new policy outcomes be achieved?

The policy outcomes are expected to be achieved by the end of 2022

- Why should I pay or get compensation?

Now, we would like to know your preference on the actions and objectives for air pollution reduction. If you would like to see the situation improve in any of the effects, then you may need to **pay extra** to fund the additional activities needed. If you would be satisfied with lower health or visibility levels, then you may **receive some of your money** back, as fewer of the planned actions would have to be undertaken.

- **A bit of scientific knowledge**

Why the effects of health and visibility are separable?

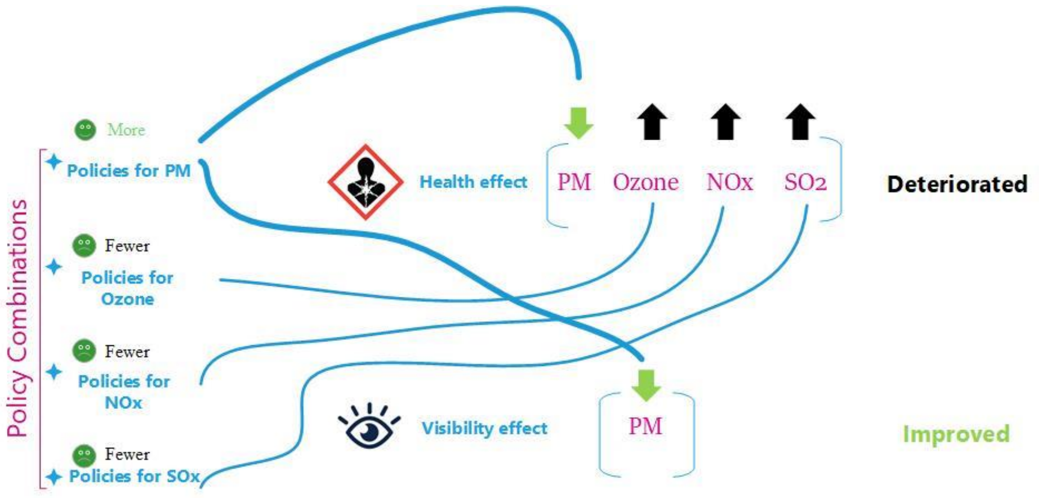
Scientists have proved that the health and visibility effects of air pollution are not necessarily related, because they have different sources. According to the reports from the United Nations and the Environmental Protection Agency of the United States, people's health is affected by detrimental substances like ozone, nitrogen oxide (NOx), particulate matter (PM) and sulphur dioxide (SO2), but visibility is mainly affected by particulate matter.

➢ Health: Ozone, NOx, PM, SO2
➢ Visibility: PM

In our context, government will implement a combination of policies to alleviate air pollution problems, and due to the limited governmental budget, a policy combination cannot target all air pollutants at the same time.

The picture (figure 1) below provides a visual example.

In the example, after implementing a policy combination, visibility issue will be alleviated while health will be aggravated, if the government implements **more** policies (compared with the current level of actions) to reduce PM, and **fewer** policies to reduce other detrimental substances, in other words, ozone, NOx and SO2. Accordingly, you need to pay extra money for the improved visibility, but will receive some of your money back due to the deteriorated health issue.



Note

PM=Particulate Matter (Including PM2.5, PM10)

NOx= Nitrogen Oxide

SO2 = Sulphur Dioxide

Figure 1: Visibility is alleviated while Health is aggravated

If more policies for PM, and fewer policies for Ozone, NOx, and SO2, Visibility will be improved, but Health will be deteriorated.

Similarly, visibility could be aggravated, but the health issue is alleviated, if the government implements more policies to reduce ozone, NOx and SO2, and fewer policies to reduce PM. Accordingly, you need to pay extra money for the improved health, but will receive some of your money back due to the deteriorated visibility issue.

[Question]: Now, do you understand that it is possible to have actions that **alleviate the health problem** but **aggravate the visibility problem** or the other way around?

- Yes, I understand
- No, I don’t understand, and would like to read the instruction again

- How is the payment change achieved?

This payment change will be achieved through an increase or decrease in your monthly household electricity, gas and heating bill. The change in your bill will be organised by state owned electric power and gas companies (for example, State Grid Corporation of China and China Gas), and they will cooperate with the local government to achieve clean air plans.

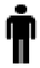
[Please read the following text patiently as it helps you to better understand the context and express your opinions.]

In order to assist the government in making policies to tackle the air pollution issue, they need to hear your voice as a citizen in your city.

The tables below show the potential air pollution effects on people, after the governmental actions are implemented.

Four different characteristics are listed: health, chance of success, visibility and payment effects. Note that these effects have a range of possible levels.

Health effects: The effect of air pollution on health in your local area. This is represented by the number of hospital admissions per year due to air pollution. The man shape icon represents 100 thousand people who go to hospital due to air pollution related diseases in your area.



Health (number of hospital admissions per year)

150,000 hospital admissions per year (**20,000** or **15% more**)
145,000 hospital admissions per year (**15,000 or 11% more**)
140,000 hospital admissions per year (**10,000 or 7.5% more**)
130,000 hospital admissions per year (no change)
120,000 hospital admissions per year (**10,000 or 7.5% less**)
115,000 hospital admissions per year (**15,000 or 11% less**)
110,000 hospital admissions per year (**20,000** or **15% less**)

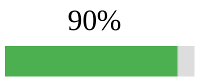
Current situation

Chance of success:

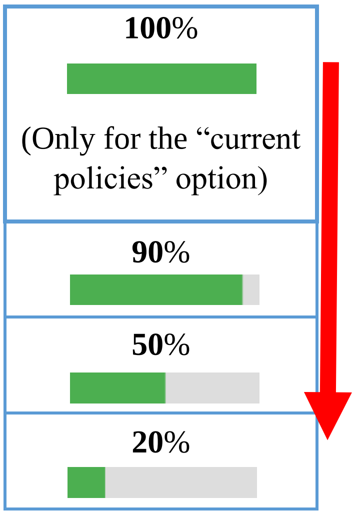
The health effect of air pollution cannot be accurately predicted. Scientists have shown that the health effect is affected by wind, rain and extreme weather events, and it is very difficult to forecast these factors.

In our context, we use chance of success to describe the accuracy of the prediction. That means there is a chance that the health improvement or deterioration will occur, but also a chance that it will not occur and the health outcome will remain at the level under the current air pollution policies, which is 130,000 hospital admissions per year.

The bar graph shows the chance that the health outcomes will be achieved. For example, the picture below shows 90%: there is a 90 out of 100 chance (shaded green) that the outcome will occur, and a 10 out of 100 chance (shaded grey) that the health outcome will not occur. In the case of not occurring, the health outcome will remain at the level under the current air pollution policies.



Chance of success



An important reminder

The chance of success represents the likelihood that the stated health outcomes will occur.

For example, if the health outcome deteriorates (in other words, the number of hospital admissions increases), higher "chance of success" means that the deteriorated situation is more likely to happen.

if the health outcome improves (in other words, the number of hospital admissions decreases), higher "chance of success" means that the improved situation is more likely to happen.

Visibility effects: The number of bad visibility days per month in your local area. On a bad visibility day, visibility on traffic roads is less than 1.5 kilometres. The picture below compares a bad visibility day (left) to a good visibility day (right).

Bad visibility ***Good visibility***

Visibility (number of bad visibility days per month)

12 days of bad visibility per month (**4** days more)
10 days of bad visibility per month (**2** days more)
8 days of bad visibility per month (no change)
6 days of bad visibility per month (**2** days less)
4 days of bad visibility per month (**4** days less)

Current situation

Electricity, gas and heating bill: Your choices of different policies are accompanied by changes in your household monthly electricity, gas and heating bill. Your monthly bill will remain unchanged if you choose to maintain the current set of actions.

Electricity, gas and heating bill change per household per month (year)	
500 RMB increase/month （**6000** RMB increase/year） 	
200 RMB increase/month （**2400** RMB increase/year ） 	
100 RMB increase/month （**1200** RMB increase/year ） 	
No change in bill	**Current situation**
100 RMB decrease/month （**1200** RMB decrease/year ） 	
300 RMB decrease/month （**3600** RMB decrease/year ） 	
500 RMB decrease/month （**6000** RMB decrease/year ） 	

Note that if the amount of bill decrease exceeds your monthly electricity, gas and heating bill, it means that you don’t need to pay any bills and the exceeding amount will be transferred to your bank account.

Please note that the **chance of success only affects the health effect** of air pollution, not the visibility effect and the change in electricity, gas and heating bill.

- A bit of scientific knowledge

Why health effect of air pollution could be uncertain, and visibility effect is certain?

The relationship between health (especially long-term health) and air pollution, is still not well predictable. In addition, factors such as personal behaviour and habits, and working environment can also affect personal health, and sometimes the consequence of a health problem is triggered by a combination of many factors. Thus, the health outcomes are uncertain.

However, particulate matter is the main factor that affects visibility, and the visibility effect is much better predictable than the health effect. So the visibility outcomes are more certain than the health outcomes, and the policies tend to be effective in a short time.

Moreover, air pollutants related to the health effect is dependent on weather conditions, but visibility effect is less dependent on weather. For example, in a sunny day, ground level ozone will be much higher than that in a rainy or cloudy day, which causes adverse effect on human's health. Thus, the health effect is more likely to be uncertain than the visibility effect, due to the unpredictable weather.

To sum up, in our context, the chance of success only affects the health effect of air pollution, not the visibility effect.

Question: Now, do you understand that the chance of success is only applied to health, while visibility and electricity, gas and heating bill are certain?

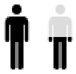
A Yes, I understand

B No, I don't understand

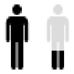
[Please read the following text patiently as it helps you to better understand the context and express your opinions.]

Now, we will show you three different policies. We want to know which of these policies you prefer the most.

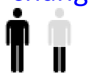
Policy A: If you choose this option, it means that there is a 90% chance that the number of hospital admissions in your city due to air pollution will be [150 thousand per year (20 thousand more (or 15% more) than the situation under the current implementation)]. Additionally, you accept 12 days of bad visibility per month instead of 8 days under the current implementation. Your monthly household electricity, gas and heating bill will reduce by 500 RMB (or 6,000 RMB annual reduction) for accepting this policy.

Attributes	**Policy A**
Health (hospital admissions/year)	**150** thousand hospital admission per year (**20** thousand more or **15%** more) 
Chance of Success	**90%**
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)
Cost per household per month (change in electricity, gas and heating bill)	**500** RMB per month bill decrease (**6000** RMB per year bill decrease) 

Policy B*:* If you choose this option, it means that there is a 20% chance that the number of hospital admissions in your city due to air pollution will be [120 thousand per year (10 thousand less (or 7.5% less) than the situation under the current implementation)]. Additionally, you accept 10 days of bad visibility per month instead of 8 days under the current implementation. Your monthly household electricity, gas and heating bill will increase by 100 RMB (or 1,200 RMB annual increase) for this policy.

Attributes	**Policy B**
Health (hospital admissions/year)	**120** thousand hospital admission per year (**10** thousand less or **7.5%** less) 
Chance of Success	**20%**
Visibility (number of bad visibility days per month)	**10** days of bad visibility per month (**2** days more)
Cost per household per month (change in electricity, gas and heating bill)	**100** RMB per month bill increase （**1200** RMB per year bill increase ） 

It is possible that you find the two policies not suitable for you, because you do not think you will benefit from them compared to the current set of actions. In that case, you may choose the **current policies**. This option would mean that you want to keep things as they are now.

Attributes	Current policies
Health (hospital admissions/year)	**130** thousand hospital admission per year (no change) 
Chance of Success	**100%**
Visibility (number of bad visibility days per month)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	No change in bill

Please be assured that there are no correct choices, we just want your opinions. Note that you may prefer other options not mentioned here to deal with air quality in your area.

Now, to understand how it works, let's do a warm-up question. Please choose the option that you prefer the most.

	Policy A	**Policy B**	**Current policies**
Health (hospital admissions/year)	**150** thousand per year (**20** thousand more or **15%** more)	**120** thousand per year (**10** thousand less or **7.5%** less)	**130** thousand per year (no change)
Chance of Success	**90%**	**20%**	**100%**
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)	**10** days of bad visibility per month (**2** days more)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	**500** RMB per month bill decrease （**6,000** RMB per year bill decrease ） 	**100** RMB per month bill increase （**1,200** RMB per year bill increase ） 	No change in bill

In the following questions, please select your most preferred policy among the three policies (Policy A, Policy B and Current policies) shown in each choice card. There are 10 questions like this. Each choice is a new situation, so please consider each new choice as independent from the previous choice you made.

Remember that although there may be someone else in your family who pays the bill for you, you need to make decisions as if you contribute to the payment too.

Please note that the chance of success only affects the health effects of air pollution, not the visibility effects and the change in electricity, gas and heating bill.

Keep in mind that if you decide to pay the extra money stated in the project you choose, the amount of money you may spend on other health and environmental programmes, and on the everyday products you buy, will be reduced. On the other hand, if you decide to accept the monetary compensation stated in the project you choose, the amount of money you may spend on other health and environmental programmes, and on the everyday products you buy, will be increased.

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Question 1

Question 2

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Question 10

Now we would like you to know more about the choices you have just made.

4. Please indicate why you choose the *current policies* option? **(multiple answers allowed)**

    A: My income is too low, so I cannot afford to pay more

    B: I think air pollution is not an important issue in my area, so there is no need to pay

    C: I don't think that the policy will be effective enough to change the air quality

    D: I don't want the air quality to be deteriorated

    E: I believe that citizens should not pay more for better air quality

    F: other reasons, please specify: _______

5. When making your choices, did you find a deterioration of health and/or visibility ever acceptable?
    A: Yes
    B: No

2.1. If no, please indicate why you think so?

    A: I don't want to sacrifice the environment, even if my gas, electricity and heating bill is reduced

    B: other reasons, please specify: _______

6. Do you think that the choices you just made were difficult or easy?

("1" is very easy; "2" is a bit easy; "3" is normal; "4" is a bit difficult; "5" is very difficult)

4. Did you find yourself ignoring any elements when making choices? **(multiple answers allowed)**

    A: I ignored the element "Health"

    B: I ignored the element "Chance of success"

    C: I ignored the element "Visibility"

    D: I ignored the element "Electricity, gas and heating bill"

    E: I considered all four elements **(exclusive)**

4.1. If you found yourself making choices only based on one or two elements, Why was this? **(multiple answers allowed)**

    A: There were too many elements that need to be considered in decision making

    B: I did not consider some elements because I don't believe they can be achieved

    C: I did not consider some elements because I don't think they are important to me

    D: Other reason, please specify______

Treatment 3 (Chapter 4)

Part 1

You will be given an introduction about air pollution in China and answer questions about how air pollution affects you and people around you

Introduction

In recent years, air pollution has become a commonly discussed issue in China. According to data from the World Health Organisation and the World Bank, over a million people in China die each year due to air pollution. The loss due to air pollution in China in 2013 was equal to 9.92% of its Gross domestic product.

There are mainly two ways in which air pollution may affect the wellbeing of people in your area:

(5) Health effect

Many substances in polluted air damage people's health, particularly the invisible small particles (e.g., PM10 and PM2.5). Inhaling these particles increases the likelihood of heart and lung diseases. Scientists have shown that air pollution is one of the most important factors that contributes to lung cancer, stroke and cardiovascular diseases. According to the Greenpeace, about 1.6 million people died in China because of diseases triggered by air pollution in 2013. In addition, air pollution in China also causes 6.8 million hospital admissions each year.

(6) Visibility effect

Severe air pollution may also cause poor visibility, and thus slow down the traffic in rush hour, delay air flights and lead to more traffic accidents in your city. Additionally, poor visibility hinders emergency and rescue operations in your city.

Now, we would like to ask you some questions about your experience of the air pollution effects.

Question 1: How often do you hear people around you talking about the health and visibility effects of air pollution in China?

A: Often
B: Sometimes
C: Never
D: I don't know

Question 2: How likely do you think it is that your health or that of your family will be affected by air pollution?

A: Very likely
B: Somewhat likely
C: Somewhat unlikely
D: Very unlikely

Question 3: Do you think you know enough about air pollution (for example, air pollutants, effects of air pollution and pollution-related policies) through social media or people around you ?

A: I know quite a lot
B: I have some knowledge about it
C: I know little about it

Question 4: Have you ever changed any of your daily activities to contribute to the reduction of air pollution? For example, have you tried to take public transport instead of driving your own car? or tried to use clean energy for home energy use?

A: Often
B: Sometimes
C: Never
D: I don't know

Part 2

Please read the introduction and answer the questions about your opinion on air pollution. Please read the following text patiently as it helps you to better understand the context and express your opinions.

There are many sources of air pollution. In order to tackle this issue in Beijing, the local government has implemented relevant policies in recent years. The key actions include shutting down polluting factories that did not reach the environmental standards set by the central government, applying new technologies to the polluting industries, and developing renewable energy, such as wind, water and solar power.

Following the Air Pollution Prevention and Control Action Plan published by the State Council of China, there are some achievements on air quality management. Data from the local environmental protection bureau shows that in the last 5 years in Beijing, the level of air pollution has been reduced by one third, which meets the target set by the central government.

Now, a decision on air pollution actions need to be made for the next five years.

- What is the current situation?

If the implementation level remains unchanged as of now, the current budget of the local government will be spent on actions to ensure that the number of hospital admissions due to air pollution in Beijing will remain at **130,000** per year, and the number of low visibility days will remain at **eight** days per month.

- What governmental actions will be taken in the future?

The actions mainly focus on the health and visibility effects of air pollution. The government may take different types of actions to deal with these two different air pollution effects. Some actions can deal with the visibility effects and some other actions can deal with the health effects, **so it is possible to have actions that alleviate health problems but aggravate visibility problems, or the other way around.**

- When will the new policy outcomes be achieved?

The policy outcomes are expected to be achieved by the end of 2022

- Why should I pay or get compensation?

Now, we would like to know your preference on the actions and objectives for air pollution reduction. If you would like to see the situation improve in any of the effects, then you may need to **pay extra** to fund the additional activities needed. If you would be satisfied with lower health or visibility levels, then you may **receive some of your money** back, as fewer of the planned actions would have to be undertaken.

- **A bit of scientific knowledge**

Why the effects of health and visibility are separable?

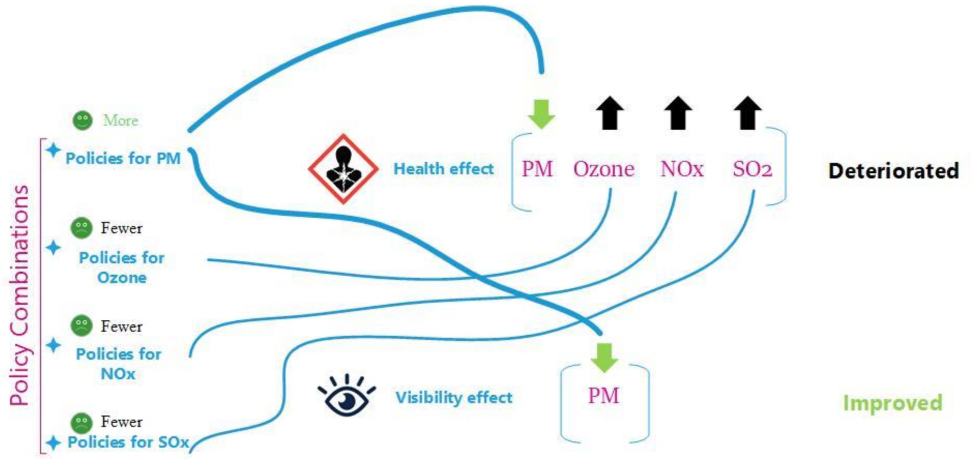
Scientists have proved that the health and visibility effects of air pollution are not necessarily related, because they have different sources. According to the reports from the United Nations and the Environmental Protection Agency of the United States, people's health is affected by detrimental substances like ozone, nitrogen oxide (NOx), particulate matter (PM) and sulphur dioxide (SO_2), but visibility is mainly affected by particulate matter.

- Health: Ozone, NOx, PM, SO2
- Visibility: PM

In our context, government will implement a combination of policies to alleviate air pollution problems, and due to the limited governmental budget, a policy combination cannot target all air pollutants at the same time.

The picture (figure 1) below provides a visual example.

In the example, after implementing a policy combination, visibility issue will be alleviated while health will be aggravated, if the government implements **more** policies (compared with the current level of actions) to reduce PM, and **fewer** policies to reduce other detrimental substances, in other words, ozone, NOx and SO2. Accordingly, you need to pay extra money for the improved visibility, but will receive some of your money back due to the deteriorated health issue.



Note

PM=Particulate Matter (Including PM2.5, PM10)

NOx= Nitrogen Oxide

SO2 = Sulphur Dioxide

Figure 1: Visibility is alleviated while Health is aggravated

If more policies for PM, and fewer policies for Ozone, NOx, and SO2, Visibility will be improved, but Health will be deteriorated.

Similarly, visibility could be aggravated, but the health issue is alleviated, if the government implements more policies to reduce ozone, NOx and SO2, and fewer policies to reduce PM. Accordingly, you need to pay extra money for the improved health, but will receive some of your money back due to the deteriorated visibility issue.

[Question]: Now, do you understand that it is possible to have actions that **alleviate the health problem** but **aggravate the visibility problem** or the other way around?

- Yes, I understand
- No, I don't understand, and would like to read the instruction again

- How is the payment change achieved?

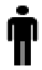
This payment change will be achieved through an increase or decrease in your monthly household electricity, gas and heating bill. The change in your bill will be organised by state owned electric power and gas companies (for example, State Grid Corporation of China and China Gas), and they will cooperate with the local government to achieve clean air plans.

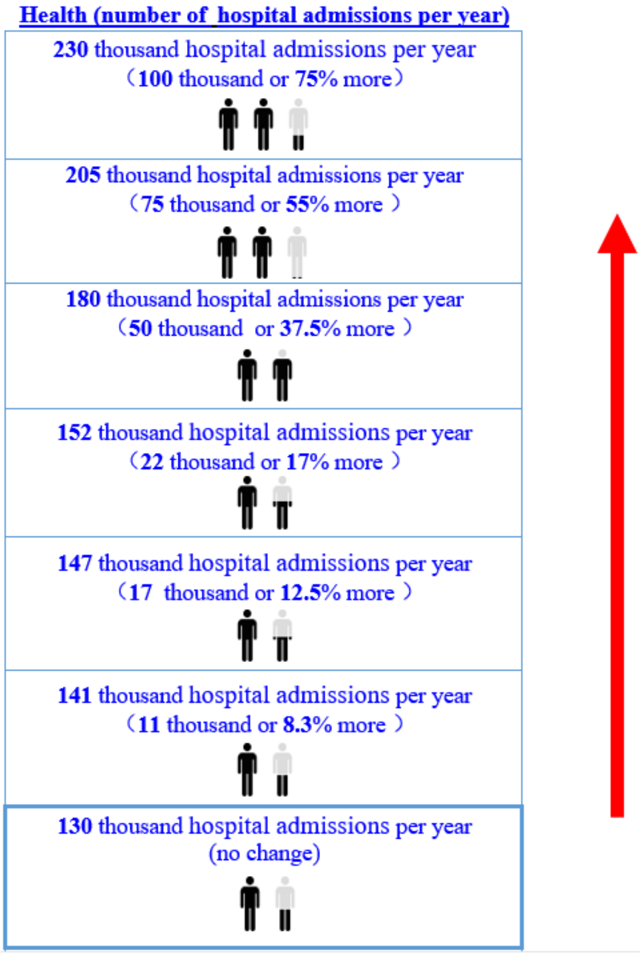
[Please read the following text patiently as it helps you to better understand the context and express your opinions.]

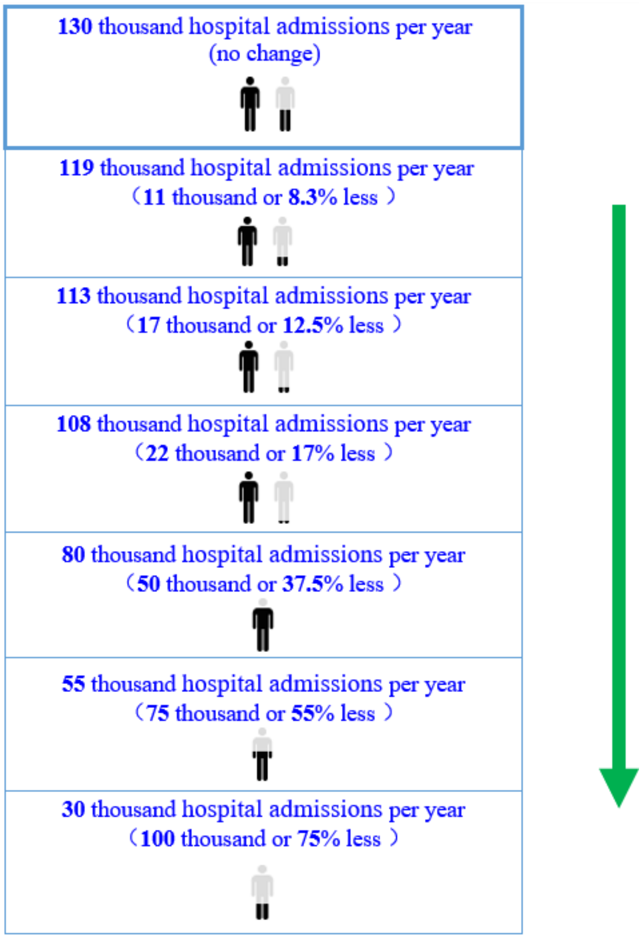
In order to assist the government in making policies to tackle the air pollution issue, they need to hear your voice as a citizen in your city.

The tables below show the potential air pollution effects on people, after the governmental actions are implemented.

Three different characteristics are listed: health, visibility, and payment effects. Note that these effects have a range of possible levels.

Health effects: The effect of air pollution on health in your local area. This is represented by the number of hospital admissions per year due to air pollution. The man shape icon represents 100 thousand people who go to hospital due to air pollution related diseases in your area. 




130 thousand hospital admissions per year
(no change)
119 thousand hospital admissions per year
（**11** thousand or **8.3**% less ）
113 thousand hospital admissions per year
（**17** thousand or **12.5**% less ）
108 thousand hospital admissions per year
（**22** thousand or **17**% less ）
80 thousand hospital admissions per year
（**50** thousand or **37.5**% less ）
55 thousand hospital admissions per year
（**75** thousand or **55**% less ）
30 thousand hospital admissions per year
（**100** thousand or **75**% less ）

Chance of success:

The health effect of air pollution cannot be accurately predicted. Scientists have shown that the health effect is affected by wind, rain and extreme weather events, and it is very difficult to forecast these factors.

In our context, we use chance of success to describe the accuracy of the prediction. That means there is a chance that the health improvement or deterioration will occur, but also a chance that it will not occur and the health outcome will remain at the level under the current air pollution policies, which is 130,000 hospital admissions per year.

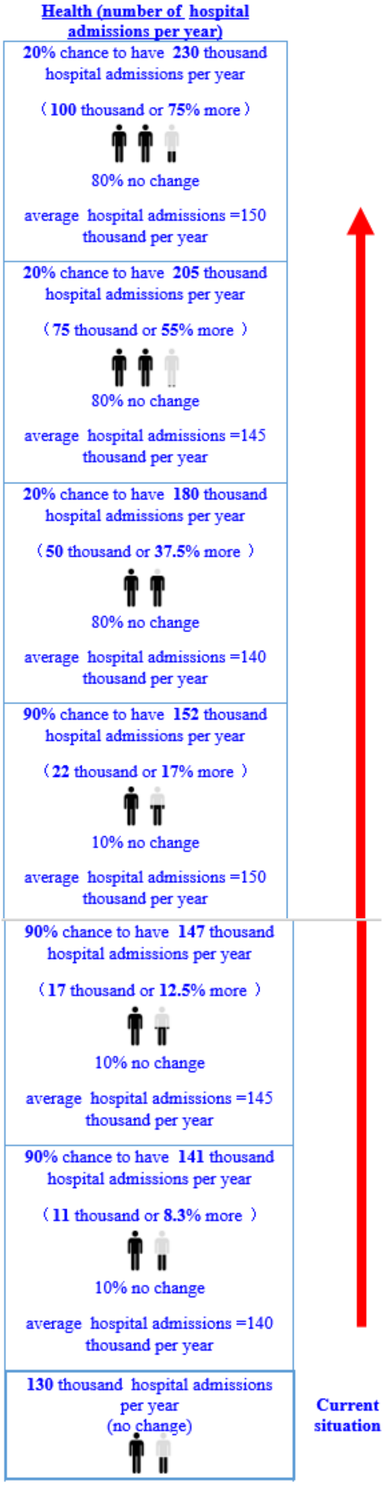
We also show the average number of hospital admissions. The average number of hospital admissions per year is the most probable outcome considering the possible outcomes and uncertainty. That means the actual number of hospital admissions may be higher or lower than the average number of hospital admissions.

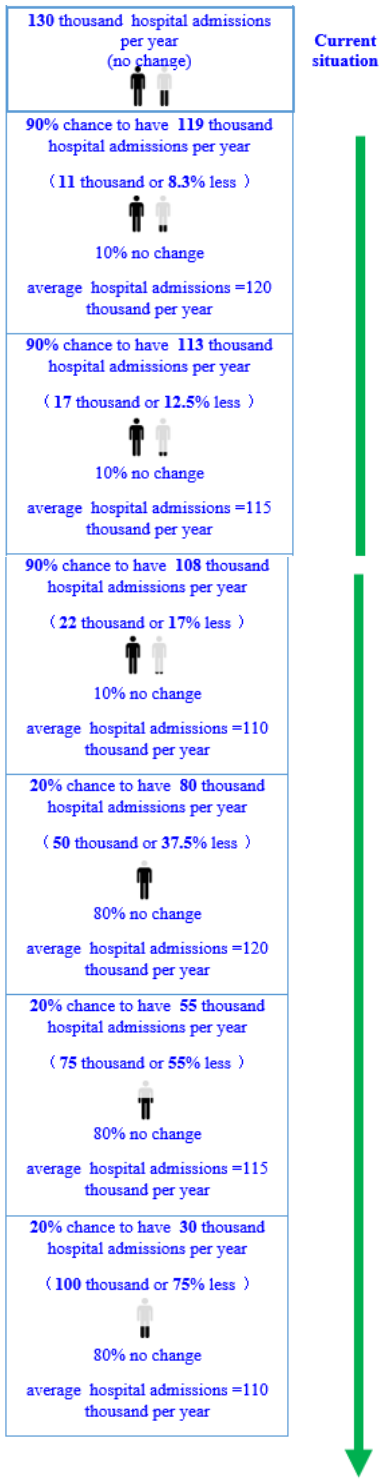
Please consider all the information, in other words, the number of hospital admissions, the chance of success, and the average number of hospital admissions, when you are asked to make your choices.

We will give you an example below:

If there is a 90% chance to have 152 thousand hospital admissions per year, and a 10% chance that the number of hospital admissions will remain at 130 thousand hospital admissions per year (in other words, remain at the level under the current air pollution policies), the average number of hospital admissions is 150 thousand hospital admissions per year. This is the calculation process of the average value:

$(90\% \times 152 + 10\% \times 130) = 150$ thousand hospital admissions per year


Health (number of hospital admissions per year)
20% chance to have 230 thousand hospital admissions per year
（100 thousand or 75% more）
80% no change
average hospital admissions =150 thousand per year
20% chance to have 205 thousand hospital admissions per year
（75 thousand or 55% more ）
80% no change
average hospital admissions =145 thousand per year
20% chance to have 180 thousand hospital admissions per year
（50 thousand or 37.5% more ）
80% no change
average hospital admissions =140 thousand per year
90% chance to have 152 thousand hospital admissions per year
（22 thousand or 17% more ）
10% no change
average hospital admissions =150 thousand per year
90% chance to have 147 thousand hospital admissions per year
（17 thousand or 12.5% more ）
10% no change
average hospital admissions =145 thousand per year
90% chance to have 141 thousand hospital admissions per year
（11 thousand or 8.3% more ）
10% no change
average hospital admissions =140 thousand per year
130 thousand hospital admissions per year
(no change)
Current situation



An important reminder

The chance of success represents the likelihood that the stated health outcomes will occur.

For example, if the health outcome deteriorates (in other words, the number of hospital admissions increases), higher “chance of success” means that the deteriorated situation is more likely to happen.

if the health outcome improves (in other words, the number of hospital admissions decreases), higher “chance of success” means that the improved situation is more likely to happen.

Visibility effects: The number of bad visibility days per month in your local area. On a bad visibility day, visibility on traffic roads is less than 1.5 kilometres. The picture below compares a bad visibility day (left) to a good visibility day (right).

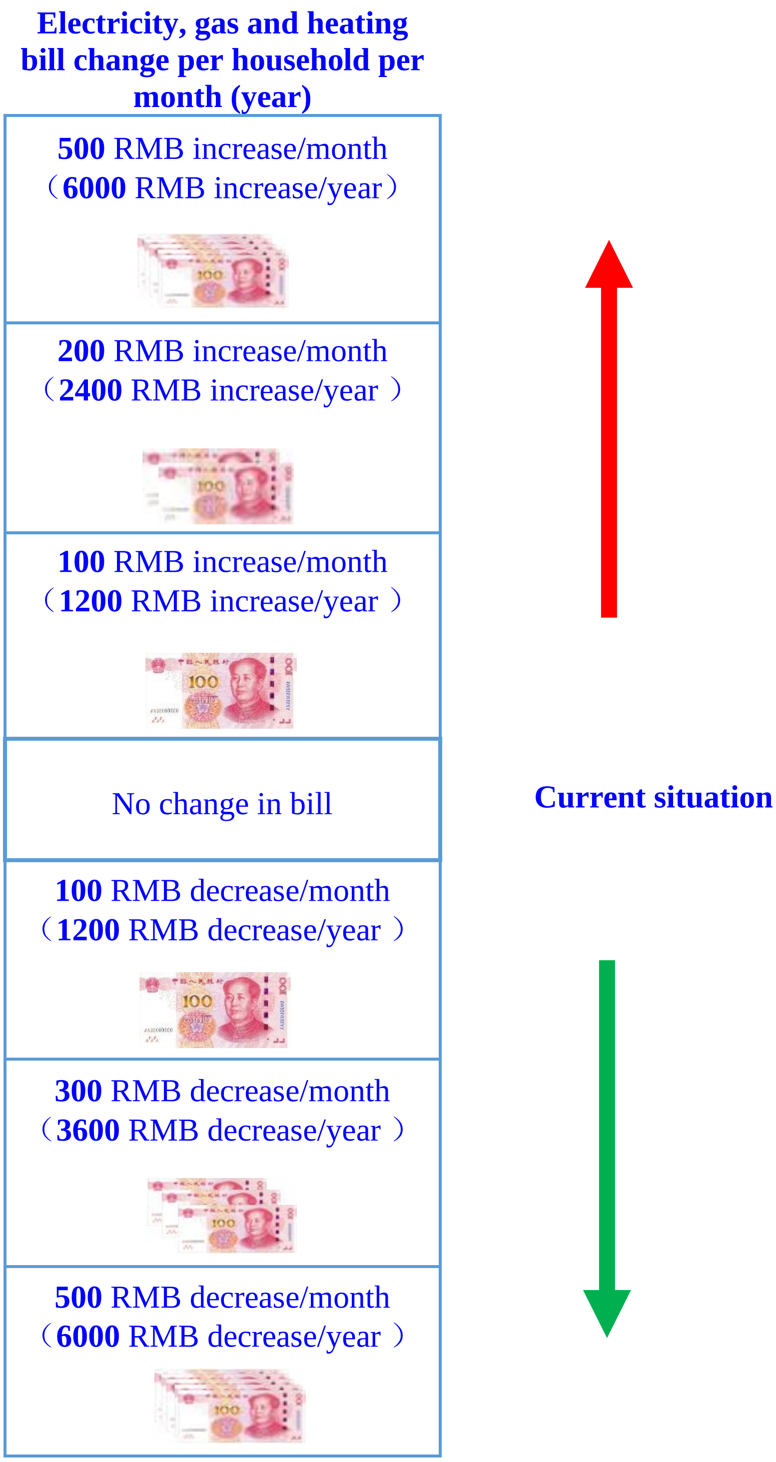
Bad visibility ***Good visibility***

Visibility (number of bad visibility days per month)

12 days of bad visibility per month (**4** days more)
10 days of bad visibility per month (**2** days more)
8 days of bad visibility per month (no change)
6 days of bad visibility per month (**2** days less)
4 days of bad visibility per month (**4** days less)

Current situation

Electricity, gas and heating bill: Your choices of different policies are accompanied by changes in your household monthly electricity, gas and heating bill. Your monthly bill will remain unchanged if you choose to maintain the current set of actions.

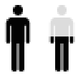


Note that if the amount of bill decrease exceeds your monthly electricity, gas and heating bill, it means that you don’t need to pay any bills and the exceeding amount will be transferred to your bank account.

[Please read the following text patiently as it helps you to better understand the context and express your opinions.]

Now, we will show you three different policies. We want to know which of these policies you prefer the most.

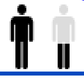
Policy A: If you choose this option, there is a 90% chance that the number of hospital admissions in your city due to air pollution will be [152 thousand per year, (22 thousand more (or 17% more) than the situation under the current implementation)], and a 10% chance that the number of hospital admissions will [remain unchanged, that is 130 thousand hospital admissions per year]. Additionally, you accept 12 days of bad visibility per month instead of 8 days under the current implementation. Your monthly household electricity, gas and heating bill will reduce by 500 RMB (or 6,000 RMB annual reduction) for accepting this policy.

Attributes	**Policy A**
Health (number of hospital admissions/year)	**90**% chance to have **152** thousand hospital admissions per year （**22 thousand** or **17**% more ）  10% chance of no change average hospital admissions =150 thousand per year
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)
Cost per household per month (change in electricity, gas and heating bill)	**500** RMB per month bill decrease （**6000** RMB per year bill decrease） 

Policy A: If you choose this option, there is a 20% chance that the number of hospital admissions in your city due to air pollution will be [80 thousand per year, (50 thousand less (or 17% less) than the situation under the current implementation)], and a 80% chance that the number of hospital admissions will [remain unchanged, that is 130 thousand hospital admissions per year]. Additionally, you accept 10 days of bad visibility per month instead of 8 days under the current implementation. Your monthly household electricity, gas and heating bill will increase by 100 RMB (or 1,200 RMB annual increase) for this policy.

Attributes	**Policy B**
Health (number of hospital admissions/year)	**20**% chance to have **80** thousand hospital admissions per year （**50** thousand or **37.5%** less ）  80% chance of no change average hospital admissions =120 thousand per year
Visibility (number of bad visibility days per month)	**10** days of bad visibility per month (**2** days more)
Cost per household per month (change in electricity, gas and heating bill)	**100** RMB per month bill increase （**1200** RMB per year bill increase ） 

It is possible that you find the two policies not suitable for you, because you do not think you will benefit from them compared to the current set of actions. In that case, you may choose the **current policies**. This option would mean that you want to keep things as they are now.

Attributes	**Current policies**
Health (hospital admissions/year)	**130** thousand hospital admissions per year (no change) 
Visibility (number of bad visibility days per month)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	No change in bill

Please be assured that there are no correct choices, we just want your opinions. Note that you may prefer other options not mentioned here to deal with air quality in your area.

Now, to understand how it works, let's do a warm-up question. Please choose the option that you prefer the most.

	Policy A	**Policy B**	**Current policies**
Health (hospital admissions/year)	**90%** chance to have **152** thousand hospital admissions per year（**22 thousand** or **17%** more ） 10% chance of no change average hospital admissions =150 thousand per year	**20%** chance to have **80** thousand hospital admissions per year（**50** thousand or **37.5%** less ） 80% chance of no change average hospital admissions =120 thousand per year	**130** thousand hospital admissions per year (no change) 
Visibility (number of bad visibility days per month)	**12** days of bad visibility per month (**4** days more)	**10** days of bad visibility per month (**2** days more)	**8** days of bad visibility per month (no change)
Cost per household per month (change in electricity, gas and heating bill)	**500** RMB per month bill decrease（**6000** RMB per year bill decrease）	**100** RMB per month bill increase（**1200** RMB per year bill increase ）	No change in bill

In the following questions, please select your most preferred policy among the three policies (Policy A, Policy B and Current policies) shown in each choice card. There are 10 questions like this. Each choice is a new situation, so please consider each new choice as independent from the previous choice you made.

Remember that although there may be someone else in your family who pays the bill for you, you need to make decisions as if you contribute to the payment too.

Please note that the chance of success only affects the health effects of air pollution, not the visibility effects and the change in electricity, gas and heating bill.

Keep in mind that if you decide to pay the extra money stated in the project you choose, the amount of money you may spend on other health and environmental programmes, and on the everyday products you buy, will be reduced. On the other hand, if you decide to accept the monetary compensation stated in the project you choose, the amount of money you may spend on other health and environmental programmes, and on the everyday products you buy, will be increased.

(PAGE BREAK HERE)

Question 1

Question 2

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Question 10

Now we would like you to know more about the choices you have just made.

1. Please indicate why you choose the *current policies* option? **(multiple answers allowed)**

    A: My income is too low, so I cannot afford to pay more

    B: I think air pollution is not an important issue in my area, so there is no need to pay

    C: I don't think that the policy will be effective enough to change the air quality

    D: I don't want the air quality to be deteriorated

    E: I believe that citizens should not pay more for better air quality

    F: other reasons, please specify: _______

2. When making your choices, did you find a deterioration of health and/or visibility ever acceptable?

    A: Yes
    B: No

2.1. If no, please indicate why you think so?

A: I don't want to sacrifice the environment, even if my gas, electricity and heating bill is reduced

B: other reasons, please specify: _______

3. Do you think that the choices you just made were difficult or easy?

("1" is very easy; "2" is a bit easy; "3" is normal; "4" is a bit difficult; "5" is very difficult)

4. Did you find yourself ignoring any elements when making choices? **(multiple answers allowed)**

A: I ignored the element "Health"

B: I ignored the element "Visibility"

C: I ignored the element "Electricity, gas and heating bill"

D: I considered all three elements **(exclusive)**

4.1. If you found yourself making choices only based on one or two elements, Why was this? **(multiple answers allowed)**

A: There were too many elements that need to be considered in decision making

B: I did not consider some elements because I don't believe they can be achieved

C: I did not consider some elements because I don't think they are important to me

D: Other reason, please specify______

5. Would you say that when you thought about the health effect, you ignored the following factors **(multiple answers allowed)**

A: Ignored hospital admissions per year

B: Ignored the chance of success

C: Ignored the average hospital admissions per year (i.e., multiplying the number of hospital admissions by the chance of success)

D: I considered all the factors **(exclusive)**

5.1 (If ignored any factors) Why did you ignore this (these) factor(s) when you thought about the health effect?

A: There were too many elements that need to be considered in decision making

C: I did not consider some elements because I don't think they are important to me

C: Other reason, please specify______

Appendix D.4.2 Chinese version

Treatment 1 (Chapter 2)

第一部分

这一部分将带您简要了解我国空气污染的现状， 并请您回答空气污染对您及周围人有何影响。

空气污染小百科

近年来，空气污染已成为我国的热门话题之一。根据世界卫生组织和世界银行的数据显示，中国每年有超过一百万人因空气污染而死亡。 此外，2013 年我国大气污染造成的福利损失相当于国内生产总值的 9.92％。

空气污染主要通过以下两种方式影响您所在地区居民的生活：

（1） 健康效应

被污染的空气中有许多物质会损害人们的健康，特别是不可见的小颗粒（如 PM10 和 PM2.5 等）。吸入这些颗粒会增加心脏和肺部疾病的发病率。

科学研究表明，空气污染是导致肺癌，中风和心血管疾病的最重要因素之一。根据绿色和平的数据显示，2013 年中国约有 160 万人死于空气污染。另外，中国因空气污染导致的急诊病历约为每年 680 万人。

（2）能见度效应

严重的空气污染也可能导致能见度低下，从而增加高峰时期的交通拥堵，航班延误，并导致您所在的城市发生更多交通事故。另外，低能见度还会妨碍您所在城市的紧急救援行动。

下面，我们将针对您的空气污染个人经历提出以下问题：

1: 您经常听到周围人讨论空气污染对健康和能见度的影响吗？

经常

有时

从没有

我不知道

2: 您认为您或者您家人的健康受到空气污染影响的可能性有多大？

很可能

有点可能

有点不可能

几乎不可能

3：您认为通过媒体或周围人有没有使您了解到足够的关于空气污染方面的知识（包括空气污染物，空气污染的影响和空气污染相关措施等）

我了解很多

我只了解一些

我基本不了解

4: 您是否曾经通过改变日常习惯来减少空气污染（比如不开私家车出门，而是选择乘坐公共交通工具；又比如尽量使用清洁能源作为家用能源）？

经常

有时

从没有

我不知道

第二部分

*在这部分中，您将阅读一段介绍，并回答有关您对空气污染政策偏好的问题。**请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字***

空气污染的来源很多，为了解决北京地区的空气污染问题，近年来地方政府实施了相关措施。大致包括关闭未达标的污染工厂；将新技术应用于煤炭、重金属等污染行业以减少污染排放；发展可再生能源，如风能，水能和太阳能等。

继国务院的“大气污染防治行动计划”出台后，北京政府已在空气质量改善方面取得了一些成绩。据来自当地环保局的数据显示，过去 5 年，北京的空气污染减少了三分之一，完成了中央政府设定的空气污染治理目标。

现在，假设政府需要制定未来 5 年空气污染治理的新计划。

- 目前的空气污染状况是什么？

若维持目前治理措施，当前空气污染治理措施能够使北京自目前起，每年因空气污染导致的急诊病例人数保持在 **13 万人**，低能见度的天数保持在每个月 **8** 天。

- 政府会采取什么样的措施？

空气污染措施主要用于治理健康效应和能见度效应。但是，由于空气污染以不同的方式对健康和能见度产生影响，因此政府会采取不同的措施来应对这两种不同的效应。

一些措施将被用于应对能见度问题，另一些措施将被用于应对健康问题。**所以，有时候可能某项措施减小了健康效应，但却加重能见度效应，有时候则相反。**

- 新措施什么时候见效？

政策目标预计将在 2022 年底之前完成。

- 我为什么需要付钱或得到补偿？

现在，我们想知道您对空气污染措施和目标的建议。与目前的治理措施相比，如果您希望看到情况得到**更进一步的改善**，由于目前预算不足，您可能需要**支付额外的费用**来支持这些额外措施。如果您觉得空气污染对健康或能见度的**影响加重**也能够接受，那么空气污染措施将比目前更少，但您可能会得到一笔相应的**资金补偿**。

❖ 科学小知识

健康效应和能见度效应为什么可以分开考虑?

科学家已经证明，由于污染物不同，空气污染对健康和能见度的影响不一定相关。

根据联合国和美国环境保护局的报告显示，空气污染的健康影响是由臭氧，氮氧化物（NOx），颗粒物和二氧化硫（SO2）等有害物质造成的，而空气污染的能见度影响主要仅受颗粒物的影响。

- 健康效应：颗粒物，臭氧，氮氧化物和二氧化硫
- 能见度效应：颗粒物

在我们的情景中，一些政策组合将被用来应对空气污染。由于政府预算有限，一个政策组合无法同时减少所有污染物。

如图 1 所示，

例如，如果公众希望提高能见度，但可以接受健康恶化，那么与目前的措施相比，**更多**的措施将被用来减少颗粒物，但**更少**的措施被用来减少其他有害物质（例如臭氧、氮氧化物、和二氧化硫）。因此，在实施这一政策组合后，能见度将得到提高，但健康影响将会恶化。相应的，您需要为能见度的提高支付额外费用，但会因为健康影响的恶化而得到一笔资金补偿。

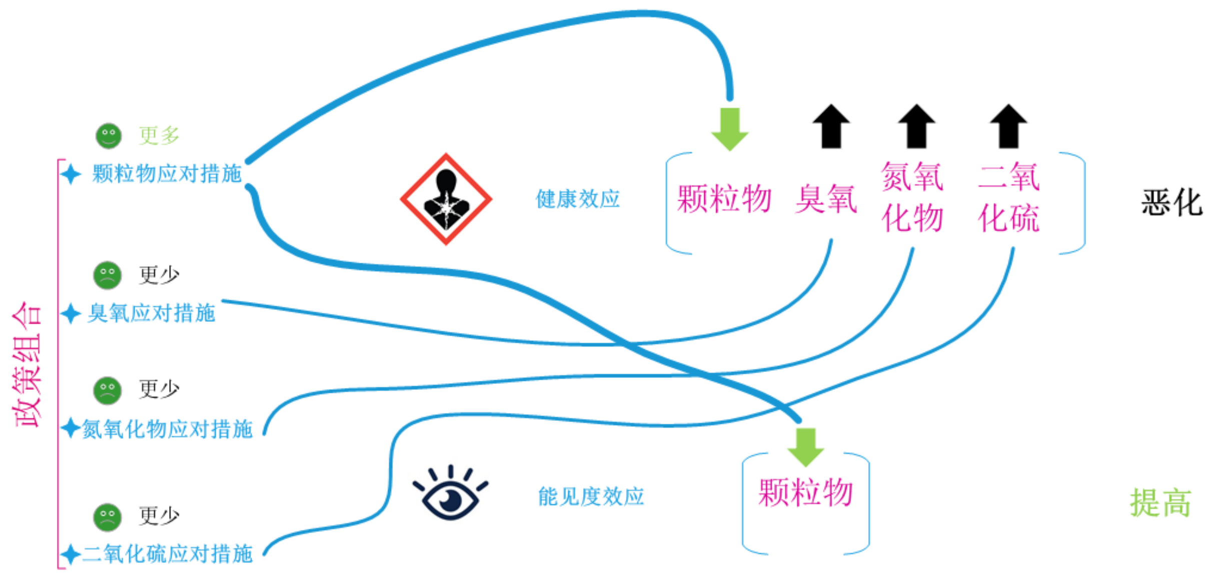


图1: 能见度效应提高，但健康效应恶化的例子

注意：颗粒物包括：PM2.5和PM10

如果采取更多措施应对颗粒物污染，更少措施应对臭氧、氮氧化物和二氧化硫污染物，那么由于颗粒物减少，能见度将得到改善，但臭氧、氮氧化物和二氧化硫的提高，健康状况可能会恶化。

同样，与目前措施相比，如果**更少**的措施将被用来减少颗粒物，但**更多**的措施被用来减少其他有害物质，则健康效应将会提高，但能见度会恶化。相应的，您需要为健康影响的提高支付额外费用，但会因为能见度的恶化而得到一笔资金补偿。

[问题]：现在，你是否理解为什么有时候某项措施使健康效应提高，但却使能见度效应恶化，有时候则相反？

A 是的，我明白

B 不，我仍然感到困惑，我想重新看一遍解释

❖ 账单变化是通过什么途径实现的?

您的账单变化是通过您每月的家庭电费，燃气及供暖费的增加或减少来实现的。国有电力和天然气公司（例如中国国家电网有限公司、中国燃气有限公司和北京热力集团等）将协助措施的实施，实现空气污染治理目标。

[请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字]

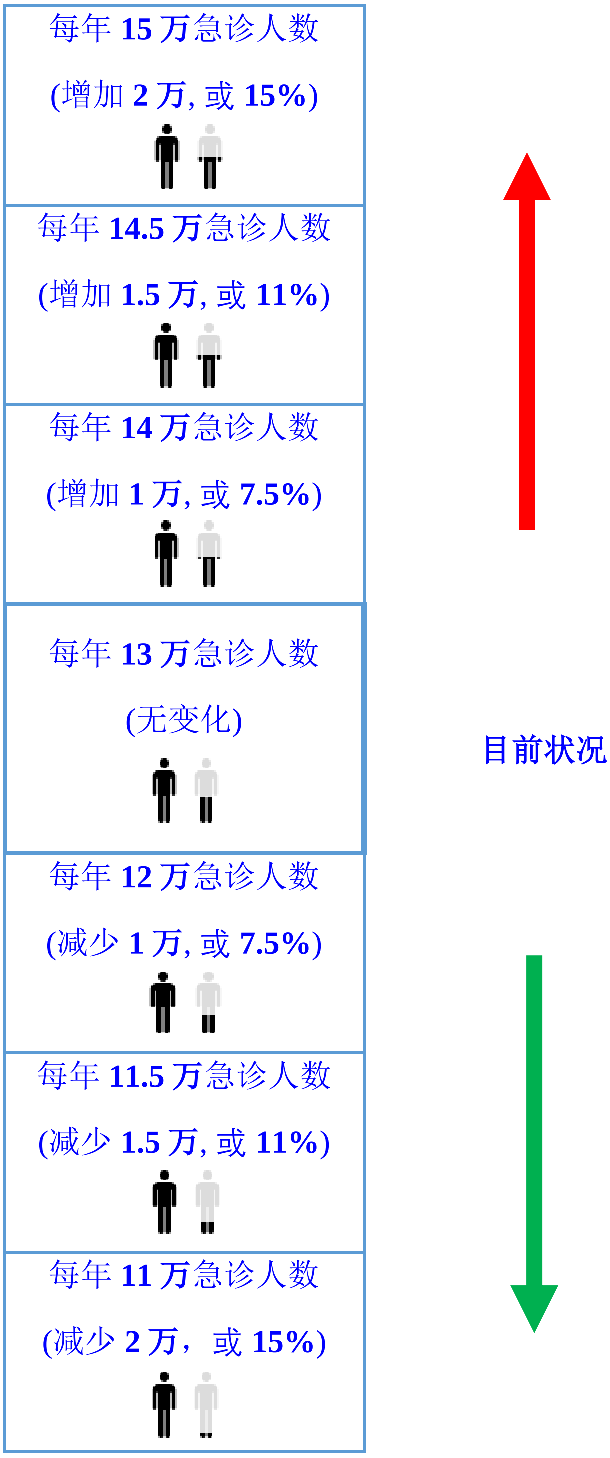
为了协助空气污染措施的制定，我们愿意了解您作为北京市民的意见。

在以下表格中，您会相关措施实施后，空气污染对您的影响可能产生的变化。具体而言，我们列出了三种影响的变化，它们是健康效应、能见度效应和您选择某措施产生的相应收支变化。

健康效应：空气污染对当地居民健康的影响。这里用空气污染导致的年急诊病例人数来表示。这个人形图案代表了您所在地区有 10 万人因空气污染导致急诊。

在后面的选择题部分，措施所达到的健康效应可能出现以下几种状况：

健康效应 (年急诊人数)


每年 15 万急诊人数
(增加 2 万, 或 15%)
每年 14.5 万急诊人数
(增加 1.5 万, 或 11%)
每年 14 万急诊人数
(增加 1 万, 或 7.5%)
每年 13 万急诊人数
(无变化)
目前状况
每年 12 万急诊人数
(减少 1 万, 或 7.5%)
每年 11.5 万急诊人数
(减少 1.5 万, 或 11%)
每年 11 万急诊人数
(减少 2 万，或 15%)

***能见度效应*：** 您所在地区每月有几天能见度“较差”。 在能见度较差的天气下，道路上的能见度不足 1.5 公里。 下图显示了能见度较好时和能见度较差时的直观比较。左图为“能见度较差”，右图为“能见度较好”。

能见度较差 ***能见度较好***

在后面的选择题部分，措施所达到的能见度效应可能出现以下几种状况：

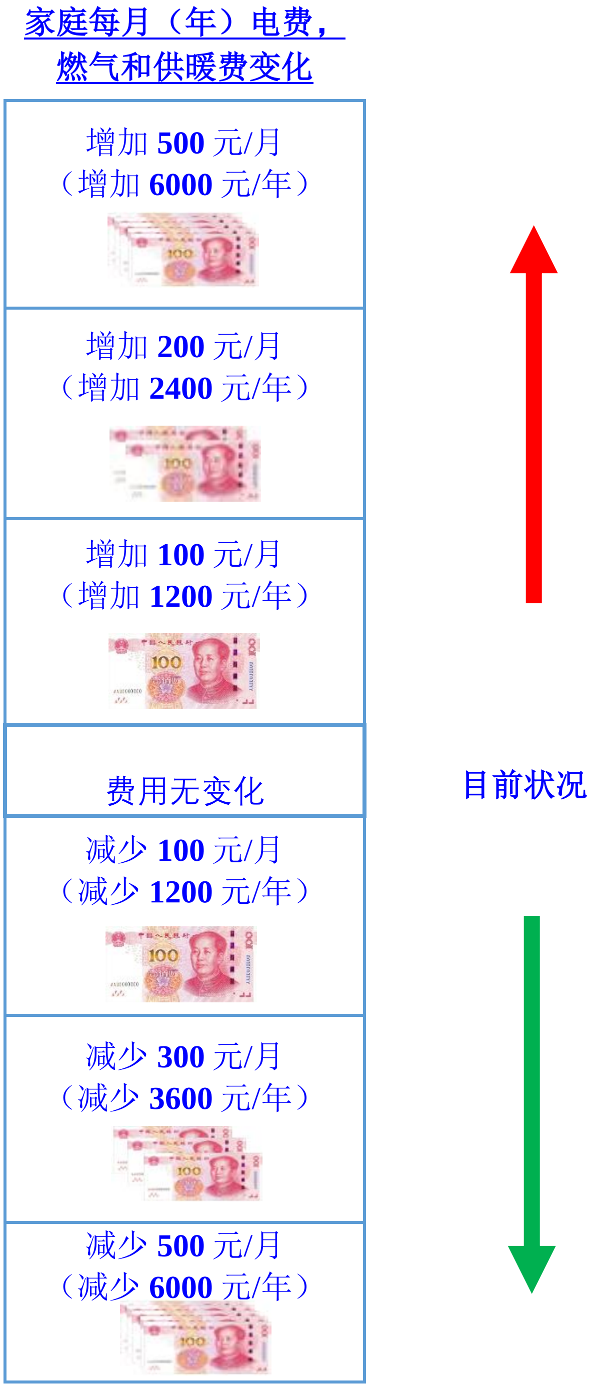
能见度效应

(每月“能见度较差”的天数)

每月有 **12** 天能见度较差 (增加 **4** 天)	
每月有 **10** 天能见度较差 (增加 **2** 天)	
每月有 **8** 天能见度较差 (无变化)	**目前状况**
每月有 **6** 天能见度较差 (减少 **2** 天)	
每月有 **4** 天能见度较差 (减少 **4** 天)	

电费，燃气和供暖费：您选择不同措施将导致家庭每月（年）电费，燃气和供暖费用的变化。 如果您选择维持目前措施，那么您的每月电费，燃气和供暖费用将保持不变。

在后面的选择题部分，措施所达到的家庭电费，燃气和供暖费可能出现以下几种状况：

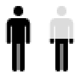


注意：若是费用减少超出了您每月支付的电费，燃气和供暖费用，您将不需要付任何电费，燃气和供暖费用，并且超出部分的补偿将自动转入您缴纳费用的银行账户上。

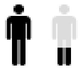
[请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字]

现在我们将向您展示三种不同的措施。 我们想知道您会选择哪种措施。

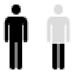
措施 A： 如果选择此选项，意味着您所在的城市每年将有 [15 万急诊人数（比目前增加 2 万人，或增加 15%] 起因于空气污染诱发的疾病，并且每月有 12 天能见度较差，而不是目前的 8 天。 接受这项措施（措施 A）之后，您每月的家庭电费，燃气和供暖费将减少 500 元（每年减少 6000 元）。

空气污染影响	**措施 A**
健康效应 (年急诊人数)	每年 **15 万**急诊人数 (增加 **2 万**，或 **15%**) 
能见度效应 (每月 “能见度较差”的天数)	每月有 **12** 天能见度较差 (增加 **4** 天)
家庭电费，燃气和供暖费变化	费用减少 **500** 元/月 （费用减少 **6000** 元/年） 

措施 B： 如果选择此选项，意味着您所在的城市每年将有 [12 万急诊人数（比目前减少 1 万，或减少 7.5%）] 起因于空气污染诱发的疾病，并且每月有 10 天能见度较差，而不是目前的 8 天。 接受这项措施（措施 B）之后，您每月的家庭电费，燃气和供暖费将增加 100 元（每年增加 1200 元）。

空气污染影响	**措施 B**
健康效应 (年急诊人数)	每年 **12 万**急诊人数 (减少 **1 万**，或 **7.5%**) 
能见度效应 (每月 “能见度较差”的天数)	每月有 **10** 天能见度较差 (增加 **2** 天)
家庭电费，燃气 和供暖费变化	费用增加 **100** 元/月 （费用增加 **1200** 元/年） 

您可能发现与目前的措施相比，以上两项措施都对您都没有好处。 在这种情况下，您可以选择**维持目前措施**。 这意味着您想要保持目前的措施不变。

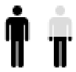
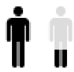
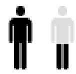
空气污染影响	**维持目前措施**
健康效应 (年急诊人数)	每年 **13 万**急诊人数 (不变) 
能见度效应 (每月 “能见度较差”的天数)	每月有 **8** 天能见度较差 (不变)
家庭电费，燃气和供暖费变化	费用不变

请记住，这些题目没有正确答案，我们只是想了解您的意见。

另外，您可能偏向一个这里没有提到的措施选项来治理您所在地区的空气污染。

另外请注意，如果您决定多付钱，这意味着您可用于其他环保项目和日常用品的支出将减少。

为了帮助您理解，让我们一起做一个热身题吧! 请在以下选择题中的三种方案里（措施 A，措施 B 和维持目前措施）选出您最喜欢的选项。

	措施 A	措施 B	维持目前措施
健康效应 (年急诊人数)	每年 **15** 万急诊人数 (增加 **2** 万，或 **15%**) 	每年 **12** 万急诊人数 (减少 **1** 万，或 **7.5%**) 	每年 **13** 万急诊人数 (不变) 
能见度效应 (每月 “能见度较差”的天数)	每月有 **12** 天能见度较差 (增加 **4** 天)	每月有 **10** 天能见度较差 **(**增加 **2** 天**)**	每月有 **8** 天能见度较差 **(**不变**)**
家庭电费，燃气和供暖费变化	费用减少 **500** 元/月 （费用减少 **6000** 元/年） 	费用增加 **100** 元/月 （费用增加 **1200** 元/年） 	费用无变化

下面让我们正式进行以上选择题的回答。请在以下选择题中的三种方案里（措施 A，措施 B 和维持目前措施）选出您最喜欢的选项。 这部分共有 10 道题目。

每道题都与之前的题目不一样， 所以请单独考虑每道题的情形。

请记住，尽管您的家庭电费，燃气和供暖费可能不是由您，而是由您家里的其他人支付。但希望您在做决定时，就像您也需要支付自己的份额一样。

最后提醒您，您选择选项的费用变化将影响您的真实收入。当您决定支付选项中的费用时，意味着您在购买日用产品或其他健康、环保相关项目的可用余额将相应减少。而当您决定接受选项中的费用补偿时，意味着您在购买日用产品和其他健康、环保相关项目的可用余额将相应增加。

第 1 题

..

..

..

..

第 10 题

现在，我们希望更多地了解您刚刚做的选择题的情况。

1. 请问您为什么会选择“维持目前措施”的选项？____ **[多选题]**

A：我的收入太低，付不起更多费用

B：我认为我所在地区的空气污染并不严重，所以我不需要付钱

C：我认为所有其它措施不一定能够有效实施

D：我不希望空气质量恶化

E：我相信市民是不需要为空气质量提高而付钱的

F：其他原因，请说明：_______

2.在做以上选择题时，您是否可以接受健康效应或能见度效应的增大（恶化）？

2.1 如果不是，请问您这么选择的原因是？

A：我认为即使减少了家庭每月（年）电费，燃气和供暖费用，我也不愿意牺牲环境

B：其他原因，请说明：_______

3.您认为您刚刚在选择题中做出决定的困难程度？

（1 很容易; 2 比较容易; 3 正常; 4 比较困难; 5 很困难）

4.您是否认为自己在刚刚做的选择题中忽略了健康效应、能见度效应、家庭每月电费，燃气费和供暖费变化这三个因素中的其中一个？**[多选题]**

A 忽略了“健康效应”

B 忽略了“能见度效应”

C 忽略了“家庭每月（年）电费，燃气和供暖费的变化”

D 三个因素都已考虑在内 **(排他)**

4.1 如果您认为自己仅依靠一个或两个因素做出选择，请问您这么做的原因是？**[多选题]**

A 做决定需要考虑的因素太多，无法兼顾

B 我没有考虑一些因素，因为我不相信它们可以实现

C 我没有考虑一些因素，因为我认为它们不重要

D 其他原因，请说明_______

Treatment 2 (Chapter 3)

第一部分

这一部分将带您简要了解我国空气污染的现状， 并请您回答空气污染对您及周围人有何影响。

空气污染小百科

近年来，空气污染已成为我国的热门话题之一。根据世界卫生组织和世界银行的数据显示，中国每年有超过一百万人因空气污染而死亡。 此外，2013 年我国大气污染造成的福利损失相当于国内生产总值的 9.92％。

空气污染主要通过以下两种方式影响您所在地区居民的生活：

（2） 健康效应

被污染的空气中有许多物质会损害人们的健康，特别是不可见的小颗粒（PM10 和 PM2.5 等）。吸入这些颗粒会增加心脏和肺部疾病的发病率。

科学研究表明，空气污染是导致肺癌，中风和心血管疾病的最重要因素之一。根据绿色和平的数据显示，2013 年中国约有 160 万人死于空气污染。另外，中国因空气污染导致的急诊病历约为每年 680 万人。

（2）能见度效应

严重的空气污染也可能导致能见度低下，从而增加高峰时期的交通拥堵，航班延误，并导致您所在的城市发生更多交通事故。另外，低能见度还会妨碍您所在城市的紧急救援行动。

下面，我们将针对您的空气污染个人经历提出以下问题：

1: 您经常听到周围人讨论空气污染对健康和能见度的影响吗？

经常

有时

从没有

我不知道

2: 您认为您或者您家人的健康受到空气污染影响的可能性有多大？

很可能

有点可能

有点不可能

几乎不可能

3：您认为通过媒体或周围人有没有使您了解到足够的关于空气污染方面的知识（包括空气污染物，空气污染的影响和空气污染相关措施等）

我了解很多

我只了解一些

我基本不了解

4: 您是否曾经通过改变日常习惯来减少空气污染，比如不开私家车出门，而是选择乘坐公共交通工具？又比如尽量使用清洁能源作为家用能源？

经常

有时

从没有

我不知道

第二部分

*在这部分中，您将阅读一段介绍，并回答有关您对空气污染政策偏好的问题。**请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字***

空气污染的来源很多，为了解决北京地区的空气污染问题，近年来地方政府实施了相关措施。大致包括关闭未达标的污染工厂；将新技术应用于煤炭、重金属等污染行业以减少污染排放；发展可再生能源，如风能，水能和太阳能等。

继国务院的“大气污染防治行动计划”出台后，北京政府已在空气质量改善方面取得了一些成绩。据来自当地环保局的数据显示，过去 5 年，北京的空气污染减少了三分之一，完成了中央政府设定的空气污染治理目标。

现在，假设政府需要制定未来 5 年空气污染治理的新计划。

❖ 目前的空气污染状况是什么？

若维持目前治理措施，当前空气污染治理措施能够使北京自目前起，每年因空气污染导致的急诊病例人数保持在 **13 万人**，低能见度的天数保持在每个月 **8** 天。

❖ 政府会采取什么样的措施？

空气污染措施主要用于治理健康效应和能见度效应。但是，由于空气污染以不同的方式对健康和能见度产生影响，因此政府会采取不同的措施来应对这两种不同的效应。

一些措施将被用于应对能见度问题，另一些措施将被用于应对健康问题。**所以，有时候可能某项措施减小了健康效应，但却加重能见度效应，有时候则相反。**

❖ 新措施什么时候见效？

政策目标预计将在 2022 年底之前完成。

❖ 我为什么需要付钱或得到补偿？

现在，我们想知道您对空气污染措施和目标的建议。与目前的治理措施相比，如果您希望看到情况得到**更进一步的改善**，由于目前预算不足，您可能需要**支付额外的费用**来支持这些额外措施。如果您觉得空气污染对健康或能见度的**影响加重**也能够接受，那么空气污染措施将比目前更少，但您可能会得到一笔相应的**资金补偿**。

❖ 科学小知识

健康效应和能见度效应为什么可以分开考虑?

科学家已经证明，由于污染物不同，空气污染对健康和能见度的影响不一定相关。

根据联合国和美国环境保护局的报告显示，空气污染的健康影响是由臭氧，氮氧化物（NOx），颗粒物和二氧化硫（SO2）等有害物质造成的，而空气污染的能见度影响主要仅受颗粒物的影响。

- 健康效应：颗粒物，臭氧，氮氧化物和二氧化硫
- 能见度效应：颗粒物

在我们的情景中，一些政策组合将被用来应对空气污染。由于政府预算有限，一个政策组合无法同时减少所有污染物。

如图 1 所示

例如，如果公众希望提高能见度，但可以接受健康恶化，那么与目前的措施相比，**更多**的措施将被用来减少颗粒物，但**更少**的措施被用来减少其他有害物质（例如臭氧、氮氧化物、和二氧化硫）。因此，在实施这一政策组合后，能见度将得到提高，但健康影响将会恶化。相应的，您需要为能见度的提高支付额外费用，但会因为健康影响的恶化而得到一笔资金补偿。

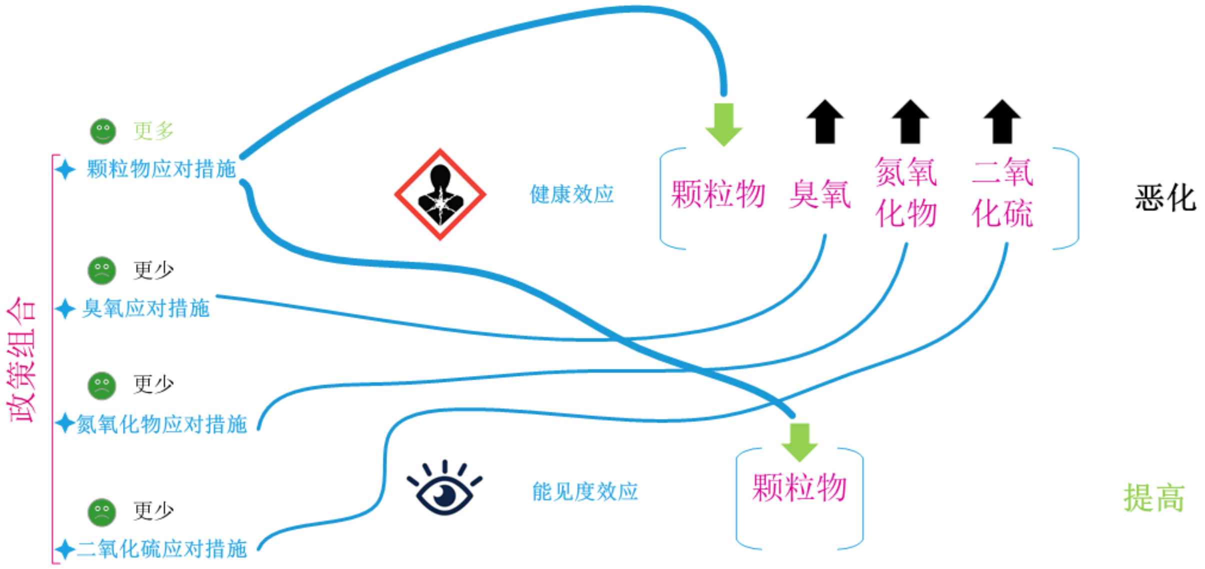


图1: 能见度效应提高，但健康效应恶化的例子

如果采取更多措施应对颗粒物污染，更少措施应对臭氧、氮氧化物和二氧化硫污染物，那么由于颗粒物减少，能见度将得到改善，但臭氧、氮氧化物和二氧化硫的提高，健康状况可能会恶化。

注意：颗粒物包括：PM2.5和PM10

同样，与目前措施相比，如果**更少**的措施将被用来减少颗粒物，但**更多**的措施被用来减少其他有害物质，则健康效应将会提高，但能见度会恶化。相应的，您需要为健康影响的提高支付额外费用，但会因为能见度的恶化而得到一笔资金补偿。

[问题]：现在，你是否理解为什么有时候某项措施使健康效应提高，但却使能见度效应恶化，有时候则相反？

A 是的，我明白

B 不是很明白

❖ 账单变化是通过什么途径实现的？

您的账单变化是通过您每月的家庭电费，燃气及供暖费的增加或减少来实现的。国有电力和天然气公司（例如中国国家电网有限公司、中国燃气有限公司和北京热力集团等）将协助措施的实施，实现空气污染治理目标。

[请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字]

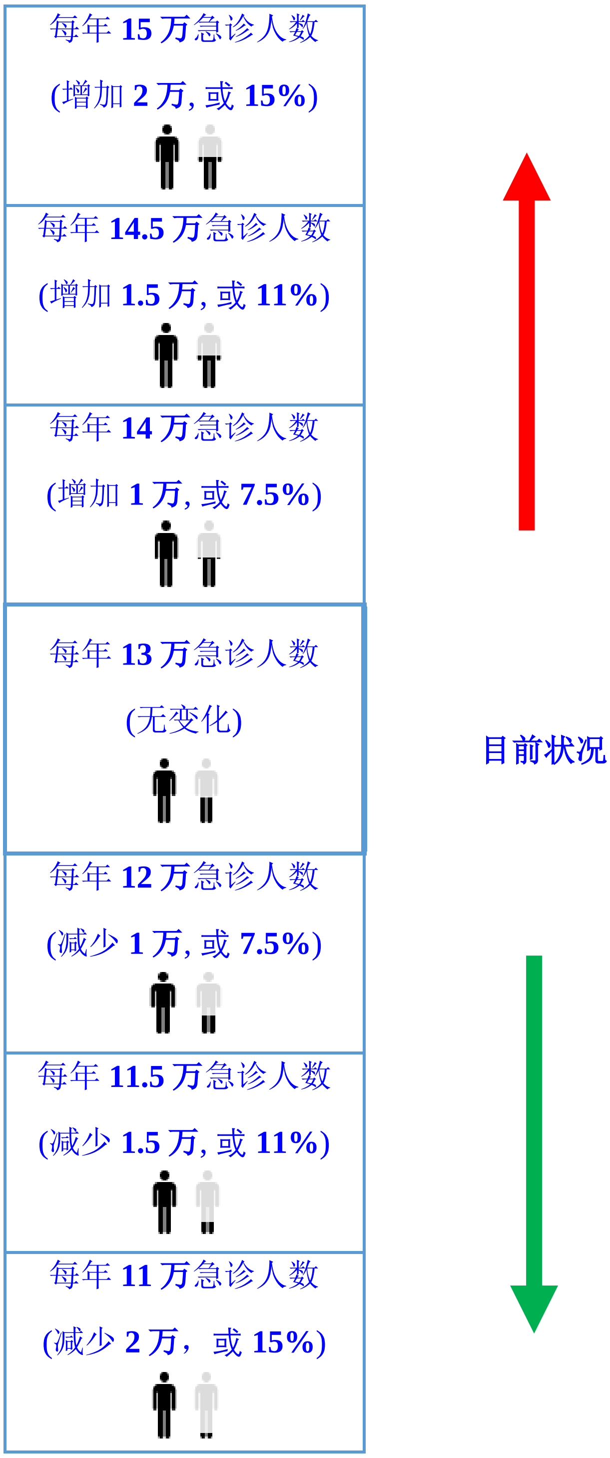
为了协助空气污染政策的制定，我们愿意了解您作为北京市民的意见。

在以下表格中，您会相关措施实施后，空气污染对您的影响可能产生的变化。具体而言，我们列出了四种影响的变化，它们是健康效应、实现的可能性、能见度效应和您选择某措施产生的相应收支变化。

健康效应：空气污染对当地居民健康的影响。这里用空气污染导致的年急诊病例人数来表示。这个人形图案代表了您所在地区有 10 万人因空气污染导致急诊。

在后面的选择题部分，措施所达到的健康效应可能出现以下几种状况：

健康效应 (年急诊人数)


每年 15 万急诊人数
(增加 2 万, 或 15%)
每年 14.5 万急诊人数
(增加 1.5 万, 或 11%)
每年 14 万急诊人数
(增加 1 万, 或 7.5%)
每年 13 万急诊人数
(无变化)
目前状况
每年 12 万急诊人数
(减少 1 万, 或 7.5%)
每年 11.5 万急诊人数
(减少 1.5 万, 或 11%)
每年 11 万急诊人数
(减少 2 万，或 15%)

实现的可能性

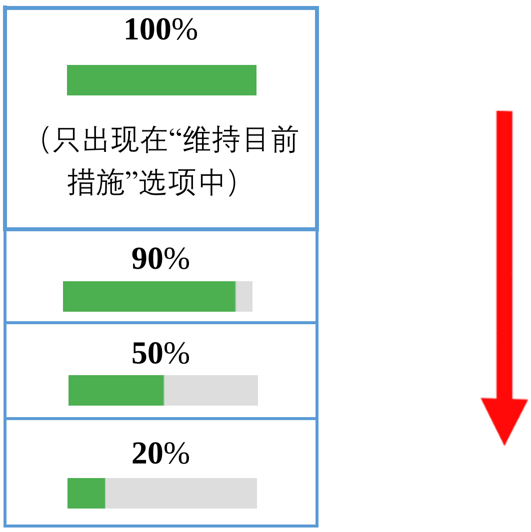
目前，空气污染的健康效应无法精确预测。科学家已经表明，空气污染的健康效应受风、雨和极端天气等自然因素的影响较大，很难预测其具体程度有多大。

在题目中，我们用措施效果实现的可能性来描述健康效应影响的精确度。这意味着上述的健康效应有一定可能性会发生，也有一定可能性不发生。若所述的健康效应没有发生，则其影响仍保持在“维持目前措施”中的健康效应水平上，即急诊人数为 13 万人。

下面这个条形图案代表了健康效应的结果发生的可能性。 例如，下面的图片表示可能性为 90％，它的意思是：有 90%的可能性（绿色部分）健康效应的结果将实现，10%的可能性（阴影灰色部分）健康效应的结果不会实现（若健康效应不会实现，则其影响仍保持在“维持目前政策”中的健康效应水平上）。

在我们的背景中，实现的可能性有以下几种情况:

<u>实现的可能性</u>



重要提示:

实现的可能性代表着健康效应中所描述的情形发生可能性的大小。

例如，如果健康效应恶化（急诊人数增加），实现的可能性越高意味着这种“健康效应恶化”情形发生的可能性越大。相应地，实现的可能性越低意味着这种“健康效应恶化”情形发生的可能性也越小。

同样地，如果健康效应提高（急诊人数减少），实现的可能性越高意味着这种“健康效应提高”情形发生的可能性越大。相应地，实现的可能性越低意味着这种“健康效应提高”情形发生的可能性也越小。

***能见度效应*：** 您所在地区每月有几天能见度“较差”。 在能见度较差的天气下，道路上的能见度不足 1.5 公里。 下图显示了能见度较好时和能见度较差时的直观比较。左图为“能见度较差”，右图为“能见度较好”。

能见度较差 ***能见度较好***

在后面的选择题部分，措施所达到的能见度效应可能出现以下几种状况：

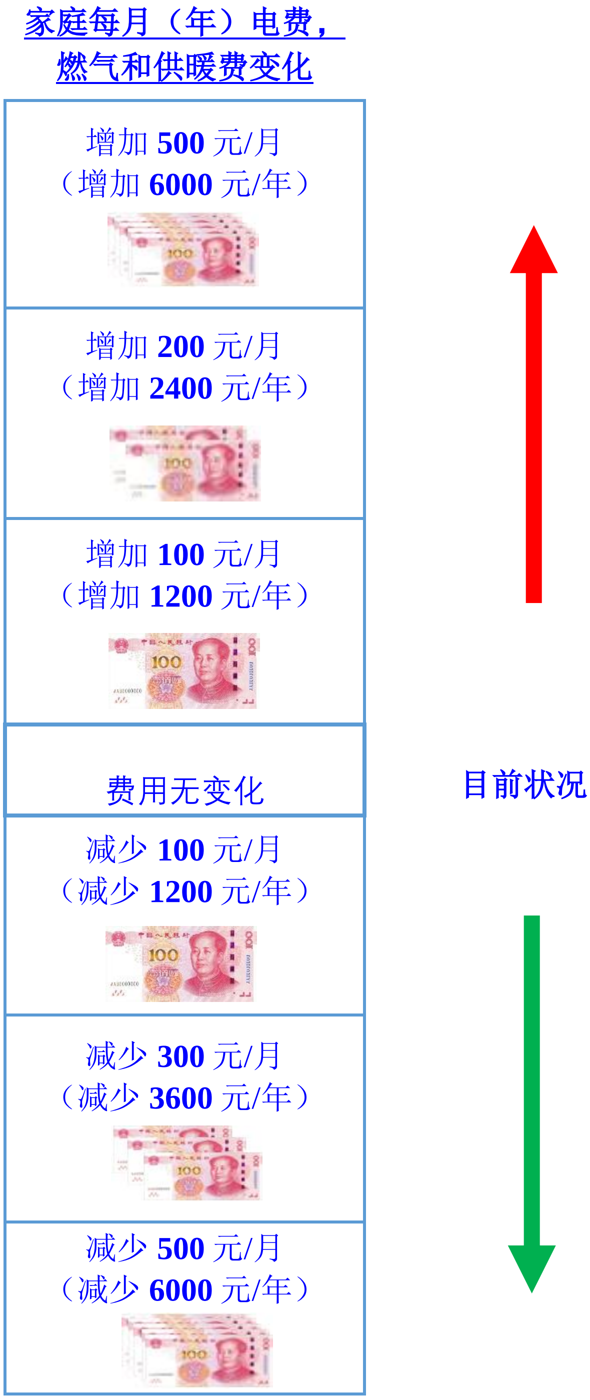
能见度效应

(每月“能见度较差”的天数)

每月有 **12** 天能见度较差 (增加 **4** 天)	
每月有 **10** 天能见度较差 (增加 **2** 天)	
每月有 **8** 天能见度较差 (无变化)	**目前状况**
每月有 **6** 天能见度较差 (减少 **2** 天)	
每月有 **4** 天能见度较差 (减少 **4** 天)	

电费，燃气和供暖费： 您选择不同措施将导致家庭每月（年）电费，燃气和供暖费用的变化。 如果您选择维持当前措施，那么您的每月电费，燃气和供暖费用将保持不变。

在后面的选择题部分，措施所达到的家庭电费，燃气和供暖费可能出现以下几种状况：



注意：若是费用减少超出了您每月支付的电费，燃气和供暖费用，您将不需要付任何电费，燃气和供暖费用，并且超出部分的补偿将自动转入您缴纳费用的银行账户上。

请注意，**实现的可能性仅适用于健康效应**。而不会影响能见度效应和电费，燃气和供暖费收支。

科学小知识：为什么空气污染对健康的影响是不确定的，而能见度的影响更为确定？

空气污染对人类健康的影响(特别是长期影响)仍然缺乏足够的科学依据，因此健康效应的不可预测性较高。比如除空气污染外，个人行为习惯和工作环境等因素都可能影响健康，有时健康效应是由多种因素共同作用的结果。因此，治理措施对健康有多大程度的影响仍尚不确定。

但是，影响能见度效应的主要因素仅为颗粒物，它并不像健康效应那样有其他复杂因素的影响，所以治理效果更好预测。因此，治理能见度效应的政策效果比健康效应更加确定，而且政策会在短时间内见效。

另外，健康效应也比能见度效应更易受天气的影响。例如，在晴朗的天气下，臭氧对人体的损害将远远多于阴天。由于天气因素较为不可预测，因此健康效应的措施效果也变得不可预测。

最终，我们设定在我们的情景中，成功可能性仅适用于健康效应，而不适用于能见度效应。

【问题】你是否理解**实现可能性**仅适用于**健康效应**，而能见度效应和电费，燃气和供暖费收支的变化则是确定的？

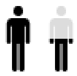
A 我明白

B 不是很明白

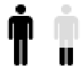
[请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字]

现在我们将向您展示三种不同的措施。 我们想知道您会选择哪种措施。

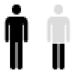
措施 A： 如果选择此选项，意味着有 90%的可能性，您所在城市每年将有[15 万急诊人数（比目前增加 2 万人，或增加 15%）] 起因于空气污染诱发的疾病，并且每月有 12 天能见度较差，而不是目前的 8 天。 接受这项措施（措施 A）之后，您每月的家庭电费，燃气和供暖费将减少 500 元（每年减少 6000 元）。

空气污染影响	**措施 A**
健康效应 **(年急诊人数)**	每年 **15 万**急诊人数 (增加 **2 万**，或 **15%)** 
实现的可能性	**90%**
能见度效应 **(每月** **“能见度较差”的天数)**	每月有 **12** 天能见度较差 (增加 **4** 天)
家庭电费，燃气和供暖费变化	费用减少 **500** 元/月 （费用减少 **6000** 元/年） 

措施 B：如果选择此选项，意味着有 20%的可能性，您所在城市每年将有[12 万急诊人数（比目前减少 1 万，或减少 7.5%）] 起因于空气污染诱发的疾病，并且每月有 10 天能见度较差，而不是目前的 8 天。接受这项措施（措施 B）之后，您每月的家庭电费，燃气和供暖费将增加 100 元（每年增加 1200 元）。

空气污染影响	**措施 B**
健康效应 (年急诊人数)	每年 **12 万**急诊人数 (减少 **1 万**，或 **7.5%**) 
实现的可能性	**20%** 
能见度效应 (每月 “能见度较差”的天数)	每月有 **10** 天能见度较差 (增加 **2** 天)
家庭电费，燃气 和供暖费变化	费用增加 **100** 元/月 （费用增加 **1200** 元/年） 

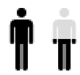
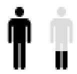
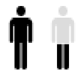
您可能发现与目前的措施相比，以上两项措施都对您都没有好处。 在这种情况下，您可以选择***维持目前措施***。 这意味着您想要保持目前的措施不变。

空气污染影响	**维持目前措施**
健康效应 (年急诊人数)	每年 **13** 万急诊人数 (不变) 
实现的可能性	**100%** 
能见度效应 (每月 “能见度较差”的天数)	每月有 **8** 天能见度较差 (不变)
家庭电费，燃气和供暖费变化	费用不变

请记住，这些题目没有正确答案，我们只是想了解您的意见。

另外，您可能偏向一个这里没有提到的措施选项来治理您所在地区的空气污染。

为了帮助您理解，让我们一起做一个热身题吧！请在以下选择题中的三种方案里（措施 A，措施 B 和维持目前措施）选出您最喜欢的选项。

	措施 A	**措施 B**	**维持目前措施**
健康效应 (年急诊人数)	每年 **15** 万急诊人数 (增加 **2** 万，或 **15%**) 	每年 **12** 万急诊人数 (减少 **1** 万，或 **7.5%**) 	每年 **13** 万急诊人数 (不变) 
实现的可能性	**90%**	**20%**	**100%**
能见度效应 (每月 "能见度较差"的天数)	每月有 **12** 天能见度较差 (增加 **4** 天)	每月有 **10** 天能见度较差 **(**增加 **2** 天**)**	每月有 **8** 天能见度较差 **(**不变**)**
家庭电费，燃气和供暖费变化	费用减少 **500** 元/月 （费用减少 **6000** 元/年） 	费用增加 **100** 元/月 （费用增加 **1200** 元/年） 	费用无变化

下面让我们正式进行以上选择题的回答。请在以下选择题中的三种方案里（措施 A，措施 B 和维持目前措施）选出您最喜欢的选项。 这部分共有 10 道题目。

每道题都与之前的题目不一样， 所以请单独考虑每道题的情形。

请记住，尽管您的家庭电费，燃气和供暖费可能不是由您，而是由您家里的其他人支付。但希望您在做决定时，就像您也需要支付自己的份额一样。

注意：实现的可能性只适用于健康效应

最后提醒您，您选择选项的费用变化将影响您的真实收入。当您决定支付选项中的费用时，意味着您在购买日用产品或其他健康、环保相关项目的可用余额将相应减少。而当您决定接受选项中的费用补偿时，意味着您在购买日用产品或其他健康、环保相关项目的可用余额将相应增加。

第 1 题

….

第 10 题

现在，我们希望更多地了解您刚刚做的选择题的情况。

1. 请问您为什么会选择“维持目前措施”的选项？____ **[多选题]**

A：我的收入太低，付不起更多费用

B：我认为我所在地区的空气污染并不严重，所以我不需要付钱

C：我认为所有其它措施不一定能够有效实施

D：我不希望空气质量恶化

E：我相信市民是不需要为空气质量提高而付钱的

F：其他原因，请说明：_______

2.在做以上选择题时，您是否可以接受健康效应或能见度效应的增大（恶化）？

2.1 如果不是，请问您这么选择的原因是？

A：我认为即使减少了家庭每月（年）电费，燃气和供暖费用，我也不愿意牺牲环境

B：其他原因，请说明：_______

3.您认为您刚刚在选择题中做出决定的困难程度？

（1 很容易; 2 比较容易; 3 正常; 4 比较困难; 5 很困难）

4.您是否认为自己在刚刚做的选择题中忽略了健康效应、能见度效应、家庭每月电费，燃气费和供暖费变化这三个因素中的其中一个？**[多选题]**

A: 忽略了“健康效应”

B: 忽略了“实现的可能性”

C: 忽略了“能见度效应”

D: 忽略了“家庭每月（年）电费，燃气和供暖费的变化”

E: 四个因素都已考虑在内 **(排他)**

4.1 如果您认为自己仅依靠一个或两个因素做出选择，请问您这么做的原因是？**[多选题]**

A: 做决定需要考虑的因素太多，无法兼顾

B: 我没有考虑一些因素，因为我不相信它们可以实现

C: 我没有考虑一些因素，因为我认为它们不重要

D: 其他原因，请说明_______

Treatment 3 (Chapter 4)

第一部分

这一部分将带您简要了解我国空气污染的现状， 并请您回答空气污染对您及周围人有何影响。

空气污染小百科

近年来，空气污染已成为我国的热门话题之一。根据世界卫生组织和世界银行的数据显示，中国每年有超过一百万人因空气污染而死亡。 此外，2013 年我国大气污染造成的福利损失相当于国内生产总值的 9.92％。

空气污染主要通过以下两种方式影响您所在地区居民的生活：

（3） 健康效应

被污染的空气中有许多物质会损害人们的健康，特别是不可见的小颗粒（PM10 和 PM2.5 等）。吸入这些颗粒会增加心脏和肺部疾病的发病率。

科学研究表明，空气污染是导致肺癌，中风和心血管疾病的最重要因素之一。根据绿色和平的数据显示，2013 年中国约有 160 万人死于空气污染。另外，中国因空气污染导致的急诊病历约为每年 680 万人。

（2）能见度效应

严重的空气污染也可能导致能见度低下，从而增加高峰时期的交通拥堵，航班延误，并导致您所在的城市发生更多交通事故。另外，低能见度还会妨碍您所在城市的紧急救援行动。

下面，我们将针对您的空气污染个人经历提出以下问题：

1: 您经常听到周围人讨论空气污染对健康和能见度的影响吗？

经常

有时

从没有

我不知道

2: 您认为您或者您家人的健康受到空气污染影响的可能性有多大？

很可能

有点可能

有点不可能

几乎不可能

3：您认为通过媒体或周围人有没有使您了解到足够的关于空气污染方面的知识（包括空气污染物，空气污染的影响和空气污染相关措施等）

我了解很多

我只了解一些

我基本不了解

4: 您是否曾经通过改变日常习惯来减少空气污染，比如不开私家车出门，而是选择乘坐公共交通工具？又比如尽量使用清洁能源作为家用能源？

经常

有时

从没有

我不知道

第二部分

*在这部分中，您将阅读一段介绍，并回答有关您对空气污染政策偏好的问题。**请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字***

空气污染的来源很多，为了解决北京地区的空气污染问题，近年来地方政府实施了相关措施。大致包括关闭未达标的污染工厂；将新技术应用于煤炭、重金属等污染行业以减少污染排放；发展可再生能源，如风能，水能和太阳能等。

继国务院的“大气污染防治行动计划”出台后，北京政府已在空气质量改善方面取得了一些成绩。据来自当地环保局的数据显示，过去 5 年，北京的空气污染减少了三分之一，完成了中央政府设定的空气污染治理目标。

现在，假设政府需要制定未来 5 年空气污染治理的新计划。

❖ 目前的空气污染状况是什么？

若维持目前治理措施，当前空气污染治理措施能够使北京自目前起，每年因空气污染导致的急诊病例人数保持在 **13 万人**，低能见度的天数保持在每个月 **8** 天。

❖ 政府会采取什么样的措施？

空气污染措施主要用于治理健康效应和能见度效应。但是，由于空气污染以不同的方式对健康和能见度产生影响，因此政府会采取不同的措施来应对这两种不同的效应。

一些措施将被用于应对能见度问题，另一些措施将被用于应对健康问题。**所以，有时候可能某项措施减小了健康效应，但却加重能见度效应，有时候则相反。**

❖ 新措施什么时候见效？

政策目标预计将在 2022 年底之前完成。

❖ 我为什么需要付钱或得到补偿？

现在，我们想知道您对空气污染措施和目标的建议。与目前的治理措施相比，如果您希望看到情况得到**更进一步的改善**，由于目前预算不足，您可能需要**支付额外的费用**来支持这些额外措施。如果您觉得空气污染对健康或能见度的**影响加重**也能够接受，那么空气污染措施将比目前更少，但您可能会得到一笔相应的**资金补偿**。

❖ 科学小知识

健康效应和能见度效应为什么可以分开考虑?

科学家已经证明，由于污染物不同，空气污染对健康和能见度的影响不一定相关。

根据联合国和美国环境保护局的报告显示，空气污染的健康影响是由臭氧，氮氧化物（NOx），颗粒物和二氧化硫（SO2）等有害物质造成的，而空气污染的能见度影响主要仅受颗粒物的影响。

- 健康效应：颗粒物，臭氧，氮氧化物和二氧化硫
- 能见度效应：颗粒物

在我们的情景中，一些政策组合将被用来应对空气污染。由于政府预算有限，一个政策组合无法同时减少所有污染物。

如图 1 所示

例如，如果公众希望提高能见度，但可以接受健康恶化，那么与目前的措施相比，**更多**的措施将被用来减少颗粒物，但**更少**的措施被用来减少其他有害物质（例如臭氧、氮氧化物、和二氧化硫）。因此，在实施这一政策组合后，能见度将得到提高，但健康影响将会恶化。相应的，您需要为能见度的提高支付额外费用，但会因为健康影响的恶化而得到一笔资金补偿。

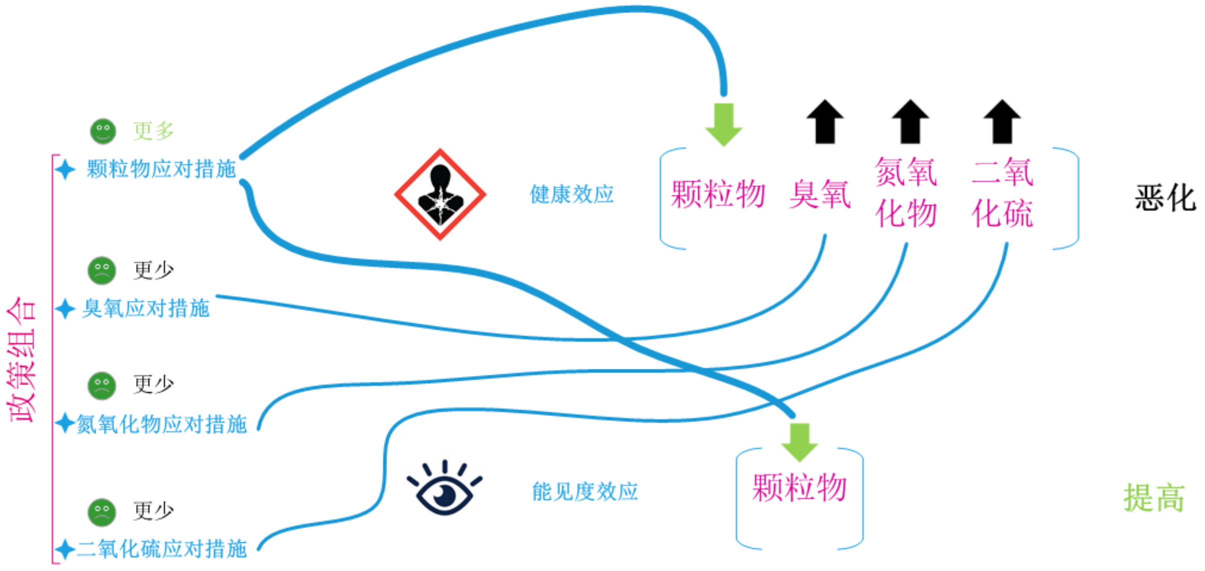


图1: 能见度效应提高，但健康效应恶化的例子

注意：颗粒物包括：PM2.5和PM10

如果采取更多措施应对颗粒物污染，更少措施应对臭氧、氮氧化物和二氧化硫污染物，那么由于颗粒物减少，能见度将得到改善，但臭氧、氮氧化物和二氧化硫的提高，健康状况可能会恶化。

同样，与目前措施相比，如果**更少**的措施将被用来减少颗粒物，但**更多**的措施被用来减少其他有害物质，则健康效应将会提高，但能见度会恶化。相应的，您需要为健康影响的提高支付额外费用，但会因为能见度的恶化而得到一笔资金补偿。

[问题]：现在，你是否理解为什么有时候某项措施使健康效应提高，但却使能见度效应恶化，有时候则相反？

A 是的，我明白

B 不是很明白

❖ 账单变化是通过什么途径实现的?

您的账单变化是通过您每月的家庭电费，燃气及供暖费的增加或减少来实现的。国有电力和天然气公司（例如中国国家电网有限公司、中国燃气有限公司和北京热力集团等）将协助措施的实施，实现空气污染治理目标。

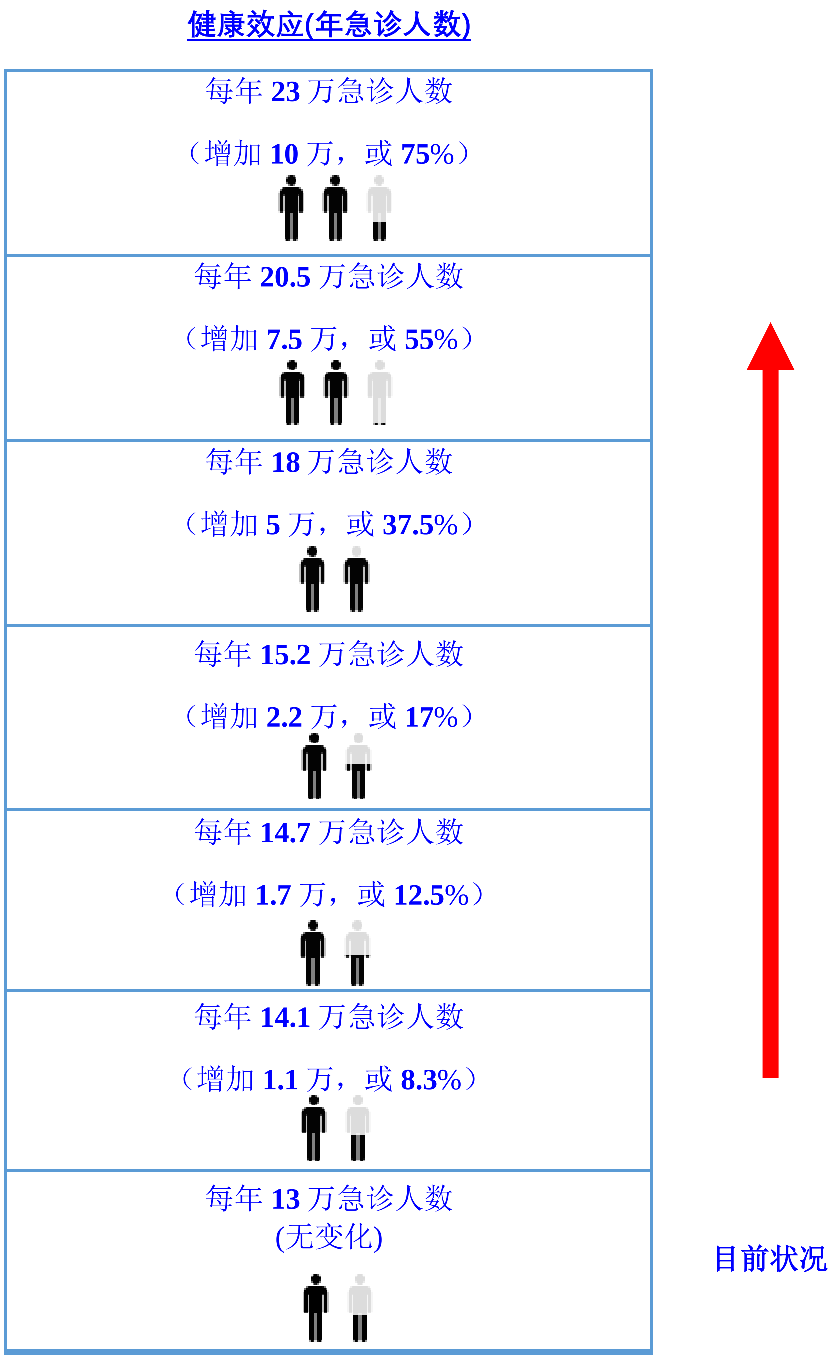
[请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字]

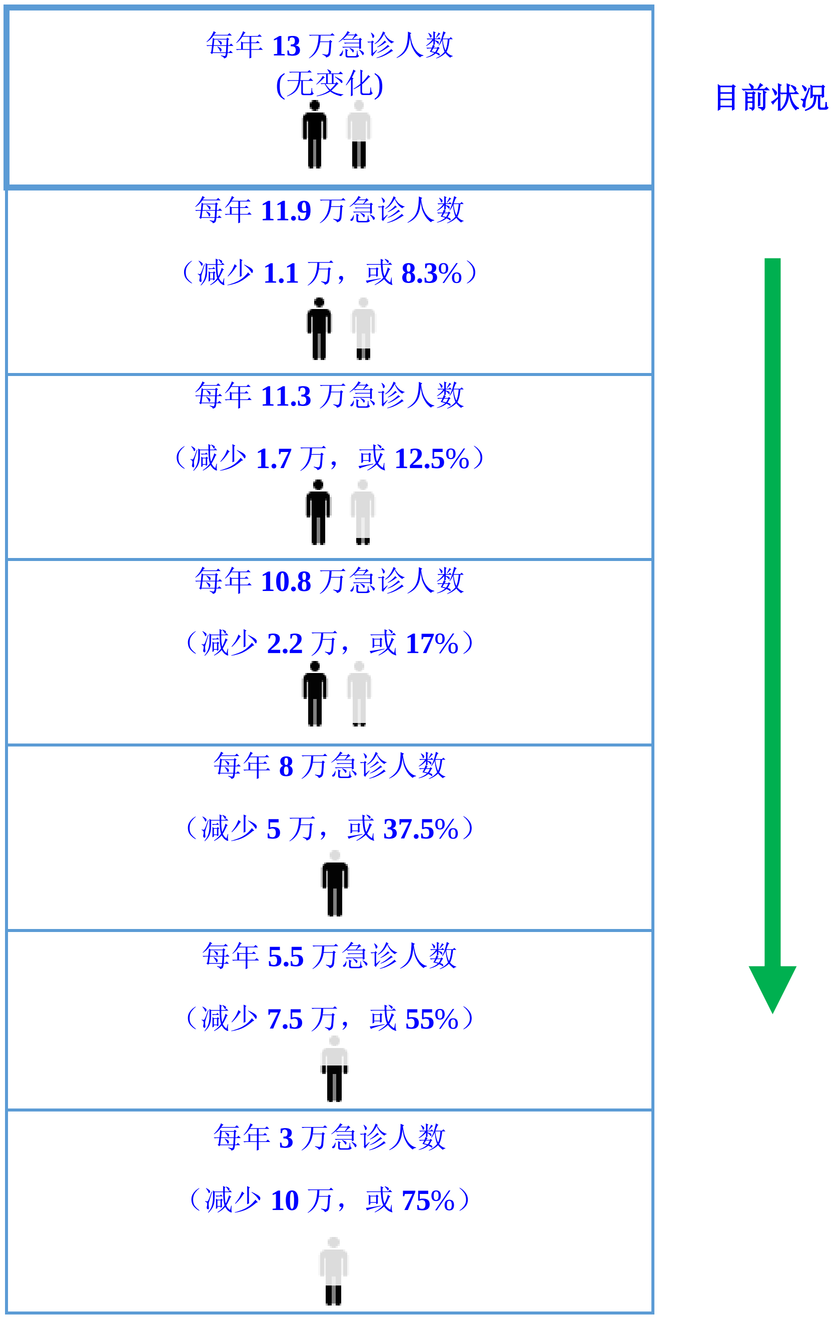
为了协助空气污染政策的制定，我们愿意了解您作为北京市民的意见。

在以下表格中，您会相关措施实施后，空气污染对您的影响可能产生的变化。具体而言，我们列出了三种影响的变化，它们是健康效应、能见度效应和您选择某措施产生的相应收支变化。

健康效应：空气污染对当地居民健康的影响。 这里用空气污染导致的年急诊病例人数来表示。这个人形图案代表了您所在地区有 10 万人因空气污染导致急诊。

在后面的选择题部分，措施所达到的健康效应可能出现以下几种状况：


健康效应(年急诊人数)
每年 23 万急诊人数
（增加 10 万，或 75%）
每年 20.5 万急诊人数
（增加 7.5 万，或 55%）
每年 18 万急诊人数
（增加 5 万，或 37.5%）
每年 15.2 万急诊人数
（增加 2.2 万，或 17%）
每年 14.7 万急诊人数
（增加 1.7 万，或 12.5%）
每年 14.1 万急诊人数
（增加 1.1 万，或 8.3%）
每年 13 万急诊人数
(无变化)
目前状况



每年 13 万急诊人数
(无变化)
目前状况
每年 11.9 万急诊人数
（减少 1.1 万，或 8.3%）
每年 11.3 万急诊人数
（减少 1.7 万，或 12.5%）
每年 10.8 万急诊人数
（减少 2.2 万，或 17%）
每年 8 万急诊人数
（减少 5 万，或 37.5%）
每年 5.5 万急诊人数
（减少 7.5 万，或 55%）
每年 3 万急诊人数
（减少 10 万，或 75%）

实现的可能性

目前，空气污染的健康效应无法精确预测。科学家已经表明，空气污染的健康效应受风、雨和极端天气等自然因素的影响较大，很难预测其具体程度有多大。

在题目中，我们用措施效果实现的可能性来描述健康效应影响的精确度。这意味着上述的健康效应有一定可能性会发生，也有一定可能性不发生。若所述的健康效应没有发生，则其影响仍保持在“维持目前措施”中的健康效应水平上，即急诊人数为 13 万人。

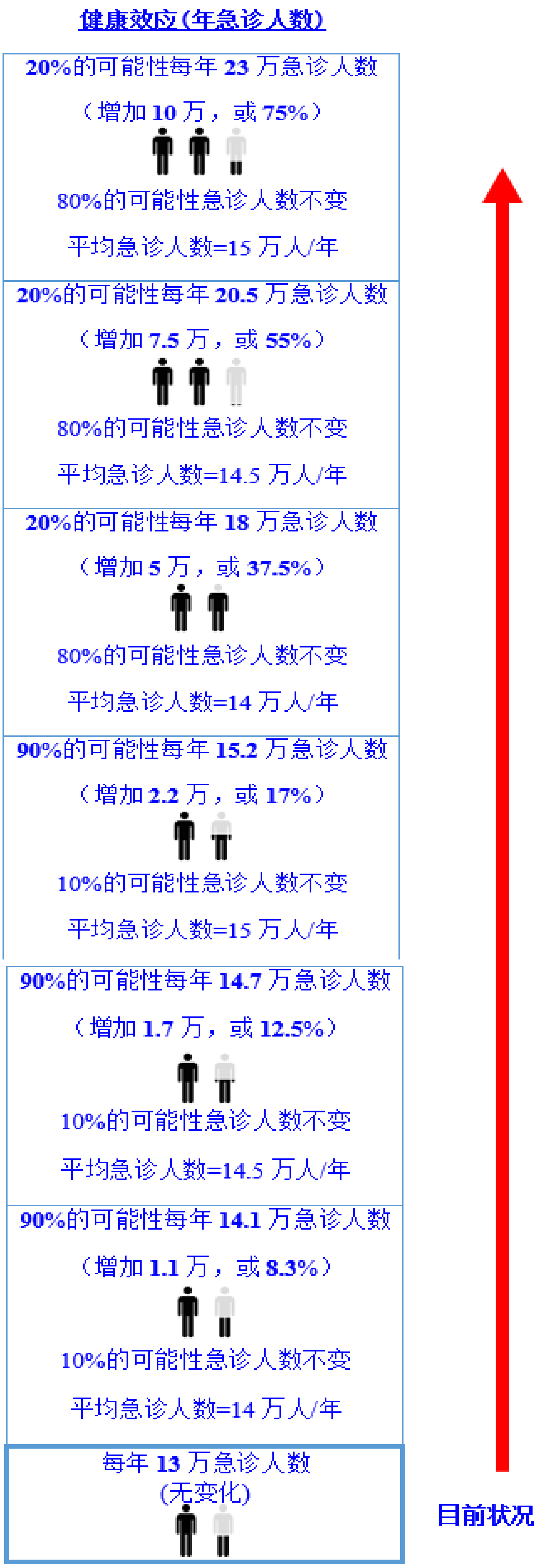
由于上述的不确定性，我们还提供了平均急诊人数的信息。 每年因空气污染而导致的平均急诊人数是一个考虑了不确定性之后，最有可能发生的健康效应结果。 这意味着实际的急诊人数可能高于或低于平均急诊人数。

当您做决定时，请将急诊人数，实现的可能性以及平均急诊人数这三个信息都考虑在您的决策中。

下面这个例子让您了解健康效应：

如果题目中的信息表明：90％的机会每年有 15.2 万急诊人数，10％的机会没有变化，即每年 13 万急诊人数（急诊人数仍保持在“维持目前措施”中的健康效应水平），平均急诊人数则为 15 万人每年。 平均急诊人数的计算过程为：

（90％× 15.2+ 10％×13）= 15 万人每年。


健康效应(年急诊人数)
20%的可能性每年 23 万急诊人数
（增加 10 万，或 75%）
80%的可能性急诊人数不变
平均急诊人数=15 万人/年
20%的可能性每年 20.5 万急诊人数
（增加 7.5 万，或 55%）
80%的可能性急诊人数不变
平均急诊人数=14.5 万人/年
20%的可能性每年 18 万急诊人数
（增加 5 万，或 37.5%）
80%的可能性急诊人数不变
平均急诊人数=14 万人/年
90%的可能性每年 15.2 万急诊人数
（增加 2.2 万，或 17%）
10%的可能性急诊人数不变
平均急诊人数=15 万人/年
90%的可能性每年 14.7 万急诊人数
（增加 1.7 万，或 12.5%）
10%的可能性急诊人数不变
平均急诊人数=14.5 万人/年
90%的可能性每年 14.1 万急诊人数
（增加 1.1 万，或 8.3%）
10%的可能性急诊人数不变
平均急诊人数=14 万人/年
每年 13 万急诊人数
(无变化)
目前状况

每年 13 万急诊人数
(无变化)

目前状况

90%的可能性每年 11.9 万急诊人数

（减少 1.1 万，或 8.3%）

10%的可能性急诊人数不变

平均急诊人数=12 万人/年

90%的可能性每年 11.3 万急诊人数

（减少 1.7 万，或 12.5%）

10%的可能性急诊人数不变

平均急诊人数=11.5 万人/年

90%的可能性每年 10.8 万急诊人数

（减少 2.2 万，或 17%）

10%的可能性急诊人数不变

平均急诊人数=11 万人/年

20%的可能性每年 8 万急诊人数

（减少 5 万，或 37.5%）

80%的可能性急诊人数不变

平均急诊人数=12 万人/年

20%的可能性每年 5.5 万急诊人数

（减少 7.5 万，或 55%）

80%的可能性急诊人数不变

平均急诊人数=11.5 万人/年

20%的可能性每年 3 万急诊人数

（减少 10 万，或 75%）

80%的可能性急诊人数不变

平均急诊人数=11 万人/年

重要提示:

实现的可能性代表着健康效应中所描述的情形发生可能性的大小。

例如，如果健康效应恶化（急诊人数增加），实现的可能性越高意味着这种“健康效应恶化”情形发生的可能性越大。相应地，实现的可能性越低意味着这种“健康效应恶化”情形发生的可能性也越小。

同样地，如果健康效应提高（急诊人数减少），实现的可能性越高意味着这种“健康效应提高”情形发生的可能性越大。相应地，实现的可能性越低意味着这种“健康效应提高”情形发生的可能性也越小。

能见度效应：您所在地区每月有几天能见度“较差”。 在能见度较差的天气下，道路上的能见度不足 1.5 公里。 下图显示了能见度较好时和能见度较差时的直观比较。左图为“能见度较差”，右图为“能见度较好”。

能见度较差 *能见度较好*

在后面的选择题部分，措施所达到的能见度效应可能出现以下几种状况：

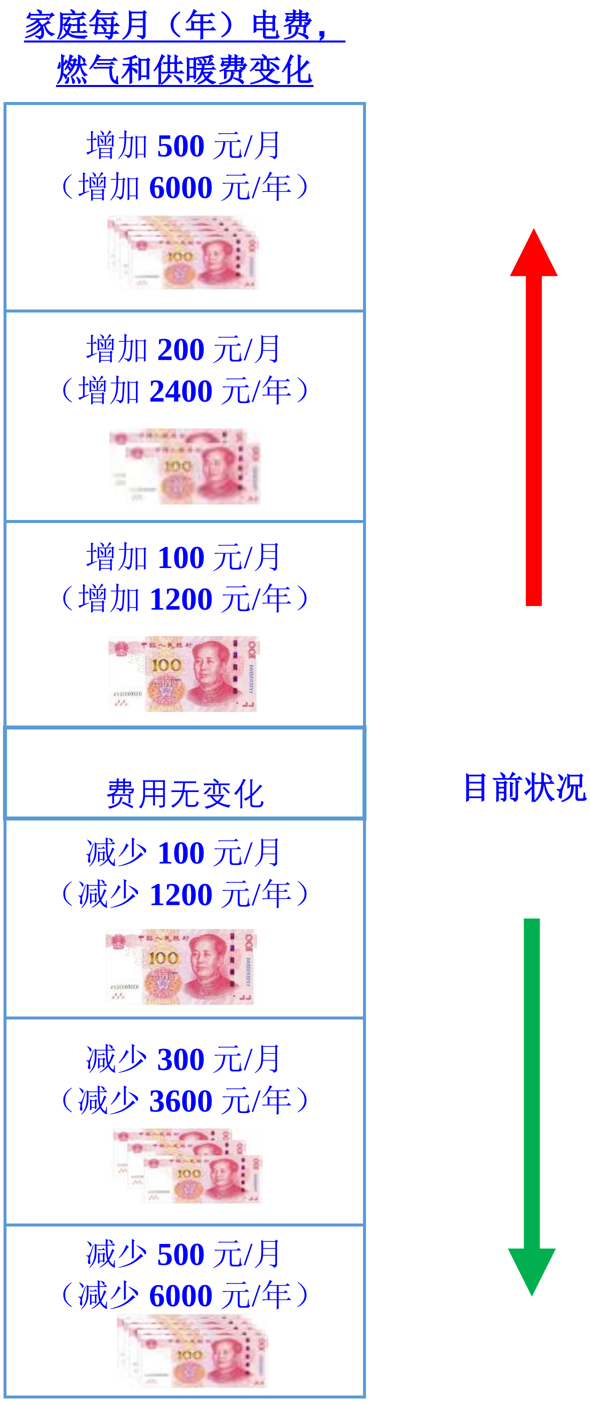
能见度效应

(每月“能见度较差”的天数)

每月有 **12** 天能见度较差 (增加 **4** 天)	
每月有 **10** 天能见度较差 (增加 **2** 天)	
每月有 **8** 天能见度较差 (无变化)	**目前状况**
每月有 **6** 天能见度较差 (减少 **2** 天)	
每月有 **4** 天能见度较差 (减少 **4** 天)	

电费，燃气和供暖费：您选择不同措施将导致家庭每月（年）电费，燃气和供暖费用的变化。 如果您选择维持当前措施，那么您的每月电费，燃气和供暖费用将保持不变。

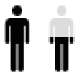
在后面的选择题部分，措施所达到的家庭电费，燃气和供暖费可能出现以下几种状况：



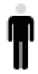
[请注意，为了您能够更好的理解后面的题目，并表达您的真实意愿，请您耐心阅读以下文字]

现在我们将向您展示三种不同的措施。 我们想知道您会选择哪种措施。

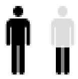
措施 A：如果选择此选项，意味着有 90%的可能性，您所在城市每年将有[15.2 万急诊人数,比目前增加 2.2 万，或增加 17%] 起因于空气污染诱发的疾病，有 10%的可能性急诊人数将[保持不变,为 13 万人/年]，并且每月有 12 天能见度较差，而不是目前的 8 天。 接受这项措施（措施 A）之后，您每月的家庭电费，燃气和供暖费将减少 500 元/月（6000 元/年）。

空气污染影响	**措施 A**
健康效应 (年急诊人数)	**90%**的可能性每年 **15.2** 人死亡 （增加 **2.2** 万，或 **17%**）  10%的可能性急诊人数不变 平均急诊人数=**15** 万人/年
能见度效应 (每月 “能见度较差” 的天数)	每月有 **12** 天能见度较差 (增加 **4** 天)
家庭电费，燃气 和供暖费变化	费用减少 **500** 元/月 （费用减少 **6000** 元/年） 

措施 B：如果选择此选项，意味着有 20%的可能性，您所在城市每年将有[8 万急诊人数，减少 5 万人，或减少 37.5%] 起因于空气污染诱发的疾病，有 80%的可能性急诊人数将[保持不变,为 13 万人/年]，并且每月有 10 能见度较差，而不是目前的 8 天。 接受这项措施（措施 B）之后，您每月的家庭电费，燃气和供暖费将增加 100 元/月（1200 元/年）。

空气污染影响	**措施 B**
健康效应 (年急诊人数)	**20%**的可能性每年 **8** 万人死亡 （减少 **5** 万，或 **37.5%**）  80%的可能性急诊人数不变 平均急诊人数=12 万人/年
能见度效应 (每月 “能见度较差” 的天数)	每月有 **10** 天能见度较差 (增加 **2** 天)
家庭电费，燃气 和供暖费变化	费用增加 **100** 元/月 （费用增加 **1200** 元/年） 

您可能发现与目前的措施相比，以上两项措施都对您都没有好处。 在这种情况下，您可以选择***维持目前措施***。 这意味着您想要保持目前的措施不变。

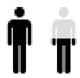
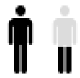
空气污染影响	**维持目前政策**
健康效应 (年急诊人数)	每年 **13** 万急诊人数 (不变) 
能见度效应 (每月 “能见度较差” 的天数)	每月有 **8** 天能见度较差 (不变)
家庭电费，燃气 和供暖费变化	费用不变

请记住，这些题目没有“正确”答案，我们只是想了解您的意见。

另外，您可能偏向一个这里没有提到的措施选项来治理您所在地区的空气污染。

为了帮助您理解，让我们一起做一个热身题吧！请在以下选择题中的三种方案里（措施 A，措施 B 和维持目前措施）选出您最喜欢的选项。

热身题

	措施 A	措施 B	维持目前措施
健康效应 (年急诊人数)	**90%**的可能性每年 **15.2** 人死亡 （增加 **2.2** 万，或 **17%**）  10%的可能性急诊人数不变 平均急诊人数=15 万人/年	**20%**的可能性每年 **8** 万人死亡 （减少 **5** 万，或 **37.5%**）  80%的可能性急诊人数不变 平均急诊人数=12 万人/年	每年 **13** 万急诊人数 (不变) 
能见度效应 (每月 “能见度较差” 天数)	每月有 **12** 天能见度较差 (增加 **4** 天)	每月有 **10** 天能见度较差 **(增加 2 天)**	每月有 **8** 天能见度较差 **(不变)**
家庭电费，燃气和供暖费变化	费用减少 **500** 元/月 （费用减少 **6000** 元/年） 	费用增加 **100** 元/月 （费用增加 **1200** 元/年） 	费用无变化

下面让我们正式进行以上选择题的回答。请在以下选择题中的三种方案里（措施 A，措施 B 和维持目前措施）选出您最喜欢的选项。 这部分共有 10 道题目。

每道题都与之前的题目不一样， 所以请单独考虑每道题的情形。

请记住，尽管您的家庭电费，燃气和供暖费可能不是由您，而是由您家里的其他人支付。但希望您在做决定时，就像您也需要支付自己的份额一样。

最后提醒您，您选择选项的费用变化将影响您的真实收入。当您决定支付选项中的费用时，意味着您在购买日用产品或其他健康、环保相关项目的可用余额将相应减少。而当您决定接受选项中的费用补偿时，意味着您在购买日用产品或其他健康、环保相关项目的可用余额将相应增加。

第 1 题

....

第 10 题

现在，我们希望更多地了解您刚刚做的选择题的情况。

1. 请问您为什么会选择"维持目前措施"的选项？____**[多选题]**

A：我的收入太低，付不起更多费用

B：我认为我所在地区的空气污染并不严重，所以我不需要付钱

C：我认为所有其它政策不一定能够有效实施

D：我不希望空气质量恶化

E：我相信市民是不需要为空气质量提高而付钱的

F：其他原因，请说明：_______

2.在做以上选择题时，您是否可以接受健康效应或能见度效应的增大（恶化）？

2.1 如果不是，请问您这么选择的原因是？

A：我认为即使减少了家庭每月（年）电费，燃气和供暖费用，我也不愿意牺牲环境

B：其他原因，请说明：_______

3.您认为您刚刚在选择题中做出决定的困难程度？

（1 很容易; 2 比较容易; 3 正常; 4 比较困难; 5 很困难）

4.您是否认为自己在刚刚做的选择题中忽略了健康效应、能见度效应、家庭每月电费，燃气费和供暖费变化这三个因素中的其中一个？**[多选题]**

A: 忽略了"健康效应"

B: 忽略了"能见度效应"

C: 忽略了"家庭每月（年）电费，燃气和供暖费的变化"

D: 三个因素都已考虑在内 **(排他)**

4.1 如果您认为自己仅依靠一个或两个因素做出选择，请问您这么做的原因是？**[多选题]**

A: 做决定需要考虑的因素太多，无法兼顾

B: 我没有考虑一些因素，因为我不相信它们可以实现

C: 我没有考虑一些因素，因为我认为它们不重要

D: 其他原因，请说明_______

5.当您考虑健康效应时，您认为您忽略了以下哪些因素？ **【多选题】**

A 忽略了每年急诊人数;

B 忽略了实现的可能性

C 忽略了平均急诊人数（这一数字由每年急诊人数乘以实现的可能性得到）

D 没有忽略以上因素**（排他）**

5.1 .请问您为什么忽略了这个（这些）因素?

A 健康效应的影响中需要考虑的因素太多，无法兼顾

B 我没有考虑一些因素，因为我认为它们不重要

C 其他原因，请说明________

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