<CN>10<en><CT>Public transport demand

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<A>10.1 INTRODUCTION

Public transport may be defined as any mode of transport available for hire and reward (Preston, 2009; Nash, 1981). In other words, any form of transport available for use by the general public. This includes not only bus and rail, but also taxis, as well as air and sea services. It can include both passenger and freight services, although own-account freight services (where a company moves its own goods) are not normally thought of as public transport. In practice, the term public transport (transit in the US) has tended to refer to land-based passenger transport and, especially, bus and rail services. It is in this context that the phrase public transport will be used in this chapter.

In the main, and like other forms for transport, public transport can be viewed as a normal consumer good. For example, the demand for public transport trips:

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* Goes up (down) when the real price of public transport falls (increases);
* Goes up (down) when real income increases (falls); and
* Goes up (down) when the real price of substitutes (e.g. car travel) increases (falls).

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However, public transport is special in that users are an important part of the production process – their time inputs (in terms of access and egress time, wait time, interchange time and in-vehicle time) can be significantly greater than their monetary inputs in terms of fares. As more public transport is produced, wait time goes down (due to increased frequencies) and access and egress time goes down (due to better network coverage), whilst interchange and in-vehicle time can go down (due to more direct routes). This is particularly true for high frequency, regular services (e.g. urban public transport). This leads to the concept of user economics of scale, as the average generalised cost of public transport will reduce as public transport demand goes up – a phenomenon known as the Mohring effect after the economist who popularised it (Mohring, 1972). It has informed the design of public transport systems, typically proscribing higher frequencies, lower fares and smaller vehicles than the norm (Jansson, 1984; Nash, 1988).

Furthermore, public transport modes may have unusual demand features. For instance, bus travel is often considered an inferior good because demand is often found to decrease as income increases, although income may be a proxy for car ownership and use. Where car ownership is controlled for, bus demand may indeed be found to increase positively with income.

In the developed world, public transport has another important feature – it is a minority mode. For example, the National Travel Survey indicates that for Great Britain in 2012, 64 per cent of trips were made by car, 22 per cent by walking, 6 per cent by local bus, 3 per cent by rail and 1 per cent by other public transport.1 Even if active travel (walking and cycling) is excluded, public transport only has a 13 per cent share of motorised trips. Of course public transport may have larger market shares in certain markets, in particular travel within major urban areas to/from the Central Business District (with public transport having a share of 90 per cent of mechanised travel to central London during the morning peak).2

In the main, the use of the classic four-stage (now five-stage if time of travel is included) land-use and transport model, as described in Chapter 9, although clearly appropriate for forecasting car travel, was perceived by public transport operators as being overly cumbersome to forecast the usage of bus and rail services. Similarly, disaggregate choice models, as described in Chapter 5, have weaknesses when dealing with minority modes (see, for example, Fowkes and Preston, 1991), although, as we will see, they have been used to examine public transport in a number of contexts.

As a result, and consistent with the thesis of public transport as a reasonably typical consumer good, the dominant approach to analysing public transport demand has been to estimate single equation elasticity models. This approach is described in the next section. However, where public transport’s base demand level is zero, this approach cannot be applied as any proportionate change will still result in zero demand. To overcome this, a set of demand forecasting approaches have been developed for new public transport services, particularly with respect to heavy rail, but also applied to light rail. These are described in section 10.3. For major cities, public transport may not be a minority mode and network models are often developed to forecast demand for a range of services. These models are described briefly in section 10.4. Lastly, some concluding comments are made in section 10.5.

<A>10.2 ELASTICITY APPROACHES

**<B>10.2.1 Basic Formulations**

The essence of the elasticity approach is to estimate product specific demand functions. For public transport, these might take the form:

Q1 = f (P1, P2, …, Pn, I, T) (10.1)

where Q1 = Quantity demanded of, for example, rail trips

P1= Price of rail travel

P2,…Pn = Price of rival products. These products might be complementary or substitutes, but more usually the latter (e.g. car, P2, and bus, P3)

I = Income

T = Taste

For transport modes one would usually replace P by GC (Generalised Cost) where GC = P + vJT and v = value of time and JT = Journey Time. For public transport, JT might be further decomposed into in-vehicle time (IVT), wait time (WT), access and egress time (usually by walking – hence WK), whilst the number of Interchanges (over and above additional walking and waiting time) might also be taken into account. Hence for public transport one might have:

GC = P + v(IVT + b WT + c WK) + dINT (10.2)

where b and c are weighting constants, which are expected to be greater than 1 (and typically around 2 for WK and 3 for WT) and d is an interchange penalty constant (which can vary greatly depending on the nature of the interchange). Reviews of values of time are given by, for example, Wardman (1998, 2004).

Elasticities are key indicators of the sensitivity of the variable of interest (in this case public transport demand) to policy variables. The most important such elasticity is the *Own Elasticity of Demand with Respect to Price (η11)* which may be expressed as:

Proportionate change in Q1 = ΔQ1/Q1 ≅ ∂ Q1 . P1 (10.3)

Proportionate change in P1 ΔP1/P1 ∂ P1 Q1

Where there are large changes (Δ) in price this is known as an arc elasticity. Where the changes are infinitesimally small (∂) this is known as a point elasticity. It is for these small marginal changes that elasticities are normally estimated.

In most respects, public transport is a normal good and we would expect the elasticity to be negative. An important threshold for price elasticity is −1. Where the absolute price elasticity is greater than 1 then demand is said to be elastic and in such circumstances price reductions will be a revenue enhancing strategy. The short-haul air market may have such features – as witnessed by the rise of the low cost carriers. Where the absolute elasticity is less than 1 then demand is inelastic, and price increases will be a revenue enhancing strategy. Urban public transport, with its frequent upward revisions in prices, may be an example of such a market.

Given our demand formulation above, the other two key elasticities are, firstly the *Own Elasticity of Demand with Respect to Income (E1I)*:

Proportionate change in Q1 = ΔQ1/Q1 ≅ ∂ Q1 .I (10.4)

Proportionate change in I Δ I / I ∂ I Q1

Transport as a whole is a normal good and the income elasticity is usually positive and often close to unity. Although this finding often also applies to rail, as we have outlined above, an exception is bus travel which can appear as an inferior good and will often have a negative income elasticity.

Second, cross elasticities examine the change in a characteristic (e.g. demand) of a good with respect to attributes (e.g. price) of a related good. The key measure will often be the *Cross Elasticity of Public Transport Demand with respect to Private Transport Price*.For example,

Proportionate change in Q1 = ΔQ1/Q1 ≅ ∂ Q1/Q1 (10.5)

Proportionate change in P2  ΔP2/P2 ∂ P2/P2

where Q1 = Rail demand and P2 = Price of car travel (often based on fuel costs).

As public transport and car travel are substitutes, this cross-elasticity is expected to be positive but the magnitude is dependent on a number of factors, particularly the relative market shares. As the car market is usually much larger than the public transport market this cross elasticity can be of a reasonable magnitude (as Q2 > Q1), although this may be offset by relatively low diversion rates (a low proportion of new car traffic is abstracted from public transport, as a large amount is generated) and a relatively low own price elasticity for car travel. This can be surmised from the following identity:

∂ Q1/Q1 ≡ ∂ Q2/Q2 ∂ Q1 Q2  (10.6)

∂ P2/P2  ∂ P2/P2  ∂ Q2 Q1

In order to estimate elasticities the most widely use functional form is the log–log or double log model. Re-writing our basic demand function (equation 10.1), this can be expressed as:

Q1 = a P1b P2c P3d Ie = ln a + b ln P1 +c ln P2 + d lnP3 + e Ln I (10.7)

Where a = mode specific constant (which incorporates the taste variable T). It should be noted that for simplicity of exposition, we have used price (P) as the main variable of interest rather than generalised cost (GC). Jorgenson and Preston (2007) give demand formulations in which P is replaced by GC, whilst the other alternative is to estimate additional parameters related to some measure of total journey time or its constituent parts, although in practice this can be difficult due to correlations between journey time and price. Elasticities from our basic double logarithmic model can be computed easily. The own price elasticity is:

η11 = (∂Q1/∂P1) (P1/Q1) = ∂ ln Q1 / ∂ ln P1 = b (10.8)

The other elasticities are also given by the estimated coefficients: c is the cross elasticity of rail demand with respect to bus price, d the cross elasticity of rail with respect to car costs and e the income elasticity. Although straightforward to estimate, this model has disadvantages in that elasticities are constant, whereas practical experience leads to expectations that these would change with the level of the policy variable – for example the own price elasticity might be expected to increase (in absolute terms) with the level of price. Furthermore, this functional is not asymptotically well behaved – at zero fares, it assumes infinite public transport demand, which means that it cannot be used to assess the effects of free concessionary fares, for example.

The main practical alternative is the negative exponential or (log-linear or semi-log) function. Again using our basic demand function this can be written as:

Q1= a exp (b P1 +c P2 + d P3 + e I), ln Q1 = ln a + b P1 c P2 + d P3 + e I, η11 = b P1 (10.9)

This gives elasticities that vary in direct proportion to the variable of interest. This may be closer to theoretical expectations but may lead to elasticities that change too quickly. The solution, used for example in the study of free concessionary bus fares in England, is to use damped elasticities (Department for Transport, 2011). This involves the estimation of a series of additional power terms that would be expected to be between 0 and 1:

Q1= a exp (b P1 f+c P2 g + d P3 h + e Ii), ln Q1 = ln a + b P1f+ c P2 g + d P3h + e I i, η11 = f b P1f (10.10)

Jansson et al. (2008, 594‒595) give a variant of this approach in a generalised cost setting. The disadvantage of this approach is that it cannot be estimated using ordinary least squares, but needs to use more sophisticated approaches such as non-linear least squares.

These functional forms can be estimated with cross-sectional data (e.g. demand data for a series of rail flows or bus route for a given point of time), time-series data (e.g. demand data for a given rail flow or bus route over a series of points in time) or a pooled dataset of time-series and cross-sectional observations. Early applications for rail in Britain include Tyler and Hassard (1973) using cross sectional data, Jones and Nichols (1983) using time-series data and Fowkes et al. (1985) using pooled data – see also Fowkes and Nash (1991). Modern ticket machines generally capture data on numbers of tickets sold by origin and destination, so data to estimate such models will be readily available to public transport operators, although not necessarily to outside researchers.

If using cross-sectional data ideally, the demand functions would be part of a system of demand and supply equations so as to overcome the identification problem. For example, is there a high level of public transport demand because of the high level of service or, conversely is there a high level of public transport service because there is a high level of demand? Similar arguments relate to fares, whilst subsidies are a further complicating factor (Frankena, 1978; Preston and Almutairi, 2013). Public transport demand might also be modelled as part of a system of demand equations, including private transport demand, to form an Almost Ideal Demand System (Coto-Millán et al., 1997). Time-series and pooled models might be affected by serial correlation and in such cases error correction and co-integration techniques might be deployed, whilst for pooled models fixed and random effect models are often tested. Wijeweera and Charles (2013) use co-integration techniques to examine time-series rail demand in Perth, Australia, but find what seem infeasibly large elasticities. Graham et al. (2009) analyse pooled data for 22 Metro systems over 13 years and compare pooled ordinary least squares, fixed effect and random effect models using the generalised method of movements estimation technique. Bresson et al. (2003) make use of similar models to analyse bus demand in France, but make use of Bayesian shrinkage estimators. Repeated studies of individual public transport users can lead to panel datasets but such studies are rare and are plagued by high attrition rates. However, many countries now have annual household travel surveys and these can be used to construct pseudo-panel data that can provide useful elasticity estimates (Tsai and Mulley, 2014).

In practice, for many public transport markets there are limited data on demand and price levels. Analysis might then be limited to a simple comparison of before (b) and after (a) levels. In such a context, we are dealing with non-marginal change and need to compute arc elasticities:

E = (∆Q/ Q)/ (∆P/P) (10.11)

The linear approximation is given by:

E ≈ [(Qa−Qb) /(Pa− Pb)] [½(Pa+ Pb)/ ½(Qa+ Qb)]. (10.12)

If expressed in natural logarithms we have:

E = (LnQa−LnQb)/(LnPa−LnPb) = Ln(Qa/Qb)/Ln(Pa/Pb) (10.13)

The bus industry often uses a variant that is referred to as the shrinkage ratio (Balcombe et al., 2004, 41):

E ≈ [(Qa−Qb) /(Pa−Pb)] [Pb/Qb)]. (10.14)

Where changes are infinitesimally small, the point and arc elasticities will be the same but they will diverge as the changes get larger. This will be particularly the case for the shrinkage ratio and related measures such as the reduction ratio or passenger resistance (in which the final Pb in equation is replaced by Pa – see Webster and Bly, 1980, Appendix III.2).

**<B>10.2.2 Applications and More Advanced Formulations**

There are a number of compendia of public transport elasticities. The then Transport and Road Research Laboratory (UK) published its *Black Book* in 1980 and the follow-up *White Book* in 2003 (Webster and Bly, 1980; Balcombe et al., 2004). The US Transportation Research Board (Pratt, 2013) the Bureau of Infrastructure, Transport and Regional Economics (Australia)3 and Victoria Transport Policy Institute (Canada)4 all publish elasticities. In the UK, the Association of Train Operating Companies’ *Passenger Demand Forecasting Handbook* (PDFH) is a useful source of rail elasticities (ATOC, 2013), whilst the *Business Case Development Manual* performs a similar role for Transport for London (TfL, 2013). For example, the PDFH examines incremental changes in rail demand using the following formulae:

Jnew = IE × IF × IT × Jbase (10.15)

where IE,IF, and IT are index numbers showing the proportionate change in journeys due to external factors, fares and generalised journey time respectively. These index numbers can then be expressed as:

 (10.16)

 (10.17)

 (10.18)

As of 2002 (version 4), with the exception of non-car ownership (NC), where the elasticity is proportional to the level of NC, the PDFH framework is based on constant elasticities, applied incrementally. Overall the framework has 10 key external elasticities, covering Gross Domestic Product per capita (replaced by Employment for key commuter markets), Population, (Non-) Car Ownership, Car Costs and Journey Time, Bus Costs and Headway and Air Costs and Headway. In addition, there are fares elasticities (see below) and generalised time (GJT) elasticities, where GJT includes journey time, along with interchange and service interval penalties, with the latter being a function of headways. It should be noted that this model system has been estimated in an ad-hoc manner through a series of separate and partial studies, as estimation of the entire function would be difficult given multicolinearity and other statistical problems.

In addition to the compendia, there have also been a number of systematic reviews of transport elasticities, originating with Oum et al. (1992) and Goodwin (1992), but also including Preston (1998), Litman (2004), Bekken and Fearnley (2005), Paulley et al. (2006), Oum et al. (2008) and Hensher (2008). This work has been extended to meta-analyses that use regression techniques to quantify the sources of variations in elasticity estimates (Nijkamp and Pepping, 1998; Kremers et al., 2002; Holmgren, 2007, Wardman, 2012, 2014). A common theme in these reviews is the large variability in public transport elasticities. In part, this may be related to the data used with large differences in the estimates from aggregate direct demand models based on revealed preference data compared with mode choice models estimated with disaggregate stated preference data. However, it also relates to the heterogeneity of the public transport market itself, with important variations by time of day/week, mode, age and ticket type.

Another feature, first popularised by Goodwin (1992), is the difference in elasticities between static models of various forms and dynamic models that explicitly take into account responses over time, leading to possibilities of lags and leads and also asymmetries of response. So far in this chapter we have considered only static models. An example of a commonly used dynamic function is the partial adjustment model (or lagged dependent variable model). Using our basic demand function (equation 10.1) this might be written as:

Q1t = aP1tb P2tc P3td Ite Q1t-1f (10.19)

where t denotes time period.

This is a double log function which can be estimated using ordinary least squares. Here, the short run price (SR) own price elasticity is estimated as b, whilst the long run (LR) price elasticity is b/(1−f) where f is between 0 and 1. The number of periods (n) to close a given proportion (p) between the SR and LR values is given by Ln (1−p)/ Ln (f). If f = 0.5, a not atypical value, 90 per cent of change occurs in 3.3 time periods and 99 per cent of change occurs in 6.6 time periods. The advantage of this approach is its simplicity, the disadvantage is that it imposes the same, regular response on all the explanatory variables.

The partial adjustment model has been widely used in both the bus and rail industry. An early application to rail was the work of Owen and Phillips (1987). Table 10.1, from Dargay and Hanly (2002), gives some illustrative results for the British bus market. There have been a number of studies that have used more complicated lagged structures (including lagged independent variables), including estimation in differences rather than levels and the use of more advanced econometric estimation techniques. However, results have been found to be sensitive to the estimation methods used and the time-period under consideration (e.g. annual compared with four-weekly data) (Preston and Dargay, 2005; Jevons et al., 2005).

[Table 10.1 about here]

Table 10.1 shows that long-run elasticities are broadly double those in the short run, which is consistent with a lagged dependent variable coefficient value (f) of 0.5. Table 10.1 suggests that bus own price elasticity increase in absolute terms, depends on the base level of fares, ranging between 0.1 and 0.8 in the short-run and 0.2 and 1.6 in the long run. The short run elasticities with respect to income, service and motoring costs are respectively around −0.4 (confirming that bus travel is an inferior good), 0.5 and 0.35.It is interesting to contrast these results with the findings of Holmgren (2007) that short run transit elasticities in the US are around −0.6 for price, 1.0 for level of service, −0.6 for income, 0.4 for petrol costs and −1.5 for car ownership. Graham et al. (2009) find for Metro rail operations that the estimated price elasticity is −0.05 in the short run and −0.33 in the long run. The estimated long run income elasticity is small but positive (0.18), indicating that metros are perceived as normal goods. The quality of service elasticities are positive and substantially higher than the absolute value of fare elasticities. Some further indications of public transport elasticities are given by Figure 10.1.

[Figure 10.1 about here]

Figure 10.1 highlights a number of features of public transport markets. They tend to be more price elastic in the long run than in the short run, more elastic in the off-peak than the peak, bus tends to be more elastic than rail (for urban travel), whilst UK markets tend to be more elastic than those overseas (possibly due to higher fare levels). There was some indication that public transport markets were becoming more elastic (as the captive market shrinks), with the short run price elasticity for bus increasing (in absolute terms) from −0.3 to −0.4.

A feature of the public transport market is that price elasticities are not the only indicator of interest. The compendia listed above give examples of elasticities with respect to in-vehicle time, service frequency/headway and cross elasticities with respect to rival public transport mode prices and car costs. Furthermore, the demand impacts of non-continuous policy variables such as information provision, new vehicles, facilities at stops etc. (sometimes referred to as ‘soft’ factors), along with semi-continuous variables (such as levels of crowding and reliability) have also been calculated. These are usually measured in terms of an equivalent change in journey time, fare or demand (Currie and Wallis, 2008; Preston et al., 2008).

One further feature of public transport elasticities is worthy of mention. Many public transport markets offer a range of ticket types. For example, for rail there are First Class and Standard Class fares, which may be Open (‘turn up and go’) or Advanced purchases (which are for a specific train). Season Tickets are also common place. For bus, there has traditionally been the distinction between travelcards and cash (Gilbert and Jalilian, 1991), whilst Pay as You Go Smartcards are increasingly coming into play. In many instance, the fare levels for each of these ticket categories are increased by the same percentage when fares are ‘revised’. Ordinary price elasticities assume that the price of one good changes but the price of all other related goods remains fixed. This is not the case in such situations. Instead, conditional elasticities are being estimated that assume that the price of all related goods change in the same proportions. These conditional elasticities can then be decomposed into the individual ordinary and cross elasticities. A stylised example, based on rail in Britain, is given by Table 10.2. For each fare category, the conditional elasticity is the sum of the ordinary own and cross elasticities.

[Table 10.2 about here]

<A>10.3 NEW SERVICES

As outlined above, an elasticity-based framework is unsuitable for use with new services where the base level of demand is zero. Blainey and Preston (2013a) have reviewed a range of approaches that may be applied to estimate rail demand in such circumstance. In the UK, this includes work by Preston (1991a, 2001) and Fowkes and Preston (1991) for local stations, by Lythgoe (2004) and Wardman et al. (2007) for interurban stations and by Jones and White (1994) for cross country services. Similar work has been carried out in other countries, such as the new station demand models calibrated by Lane et al. (2006) in the US, and work on station access and station choice carried out by Brons et al. (2009) and Debrezion et al. (2009) in the Netherlands. There has also been a great deal of work in recent years on demand forecasting for high speed rail, for example by Ben-Akiva et al. (2010) and HS2 Ltd (2012). We review here three broad types of models that have emerged out of this work: trip end, flow and choice models.

**<B>10.3.1 Trip End Models**

The simplest approach is to develop trip rate models which are simply the number of rail or bus trips made from (or to) a particular stop divided by some representation of the catchment area characteristics (usually population). These can be extended for form trip end models, which are regression models which forecast annual trips at a station based on a number of explanatory variables. Work by Blainey (2010) tested over 100 model forms on a dataset of 1,499 existing local railway stations in England and Wales with a range of datasets brought together in a GIS including freely available data on total station usage and Ordnance Survey mapping data provided under the OpenData initiative. Calibration of the models using Geographically Weighted Regression (GWR) (Fotheringham et al., 2002) allowed spatial variations in the effect of the explanatory variables on model demand to be explicitly accounted for by the model, and the best model form (2) explained 82.4 per cent of the variation in the calibration dataset (Blainey, 2009):

(10.20)

where:

= estimated number of passenger entries and exits per year at station *i*

*Pa* = resident population in output area *a*

*(a,…,n)* = output areas whose closest station by car travel time is station *i*

*wa* = weight attached to population unit *a*, given by (*t* + 1)-3.25 (a large number of weighting functions were tested, with this one giving the best model fit)

*t* = road travel time from population unit *a* to its closest station

*Fi* = train frequency at station *i* over a normal weekday

*T* = distance in km from station *i* to the nearest non-local station

*Ji4* = number of jobs located within 4 minutes’ drive of station *i*

*Pki* = number of parking spaces at station *i*

*Bi* = dummy variable taking the value e1 if Station *i* is a Travelcard boundary station, and e0 otherwise

*Tei* = dummy variable taking the value e1 if Station *i* is a terminus, and e0 otherwise

*Eli* = dummy variable taking the value e0 if Station *i* is served by electric trains, and e0 otherwise

*α*, *β*, *δ*, *τ*, *ρ*, *η*, *κ* and *ν* are parameters determined during calibration

This model was developed into a demand forecasting spreadsheet, which was used to predict demand at the 421 sites in Britain identified using a specially developed site selection procedure. It suggested that 144 of these sites would be used by over 100,000 passengers per year, putting them above around 37 per cent of existing stations. Such stations are likely to be those with the greatest case for construction, although further analysis would be necessary to confirm this, as the service patterns from the new station and resultant level of accessibility to key destinations will play a significant role in determining demand levels.

Flow level models (described below) can account for such factors, and should therefore give a more accurate indication of station viability. However, such models are more computationally complex and have much greater data requirements, including flow level ticket sales data which is not in the public domain. The trip end forecasts are in contrast simple to produce using data which is all readily available online, and therefore provide a quick means of checking the likely viability of a large number of potential sites for new stations.

**<B>10.3.2 Flow Level Models**

To forecast the revenue generated by new stations and to understand the impact additional passengers will have on rail services, it is necessary to model the distribution of trips to destinations. Blainey and Preston (2013a) describe a range of flow level models, of two main types, non-linear intervening opportunity trip distribution models (see Kanafani, 1983), and direct demand regression models (Blainey and Preston, 2010a). These were based on ticket sales data, which gives the number of tickets of different types sold between particular station pairs. While the trip distribution models seemed intuitively to be more realistic, as they were able to account for the effects of intervening opportunities and as probability-based models automatically constrain the total number of trips to be equal to that predicted by the trip end models, the direct demand models had a better fit with the observed data. This fit was further improved by recalibrating the models using GWR, with the coordinates of the origin stations used to define the spatial location of the flows (Blainey and Preston, 2010b), allowing Model (3) to explain 67 per cent of the variation across 1,289 flows from 68 stations in South East Wales.

(10.22)

where:

is the predicted number of trips per year made from station *i* to station *j*

*Exj* is the total number of trips ending at station *j* in the year being modelled

*Dij* is the straight line distance (in km) from station *i* to station *j*

*Rsij* is the rail journey time from station *i* to station *j* divided by *Dij*

*Csij* is the car journey time from station *i* to station *j* divided by *Dij*

*Hij* is the service headway in minutes between station *i* and station *j*

*Rfkmij* is the fare per rail km for travel from station *i* to station *j*

*α*, *β*, *τ*, *ρ*, *γ*, *ω*, *δ*, *κ*, *η* and *λ* are parameters determined during calibration.

The use of GWR in direct demand models appears to have great potential for enhancing the flow level forecasting of rail demand, by enabling local variations in the effect of parameters on rail demand to be taken into account. Although Model (22) is still in need of some refinement, no previous flow level model has been able to account for such spatial variations in the factors influencing demand. While the *Exj* variable might seem to introduce circularity into the model, as a new station would increase total trips to the destination, as the variable is not a constraint it in fact forms an effective proxy for destination attractiveness. A potential limitation is that the sum of predictions across all flows from a station will not necessarily sum to be equal to the prediction for that station from the trip end model. It would be simple to apply a scaling factor to the flow level results if such a constraint was felt to be desirable, but it is likely that the difference in predictions occurs because the direct demand model takes into account the influence of service patterns and accessibility to particular destinations on demand, meaning that it gives a more accurate prediction of total station usage. The models described here would require recalibration before being used in areas other than that which it was calibrated, but there is no fundamental reason why the general model forms should not be equally valid in other geographic contexts. The main constraints on the use of direct demand models are likely to be the availability of (commercially confidential) ticket sales data for calibration, and the time required for assembly of the large and complex calibration datasets. Related work using GWR has involved the calculation of elasticities for existing services (Blainey and Preston, 2013b).

**<B>10.3.3 Choice Models**

The approaches discussed above are aggregate models based on zonal data. However, such an approach has a particular weakness for public transport – some of the key variables (such as walk and wait time) may show more intra- than inter-zonal variation. Therefore, disaggregate models based on household or individual data have some appeal, although will require household travel diary data in order to calibrate and validate the models. The workhorse of these choice approaches has been the multinomial logit (MNL) model. Early applications included the work of Domencich and McFadden (1975) in Pittsburgh and Richards and Ben-Akiva (1975) in Eindhoven, whilst Dunne (1984) illustrated how elasticities can be derived from these models.

However, the MNL model is affected by the independence of irrelevant alternative axiom that prevents differential patterns of substitution (Ortuzar and Willumsen, 2011, 234). The relevance of this to public transport can be ascertained by its alternate description as the ‘red bus, blue bus’ problem (Mayberry, 1973). Suppose bus as a mode has been artificially split between red buses and blue buses. These new (but irrelevant) modes of travel will draw demand in equal proportions from all modes – when in practice they would be expected to draw demand from each other more than from other modes.

The traditional solution to this problem was to develop hierarchical logit models which group together similar alternatives in nests. For example, bus and train are often grouped together in a public transport nest (see, for example, Preston, 1991a). Initial choice models were based on revealed preference data but this had a number of weaknesses, including limited knowledge about alternatives to the mode actually used, correlations between times and costs and limited variation in variables of interest. Furthermore, revealed preference data is not available in choice contexts where the public transport mode of interest, such as light rail, guided bus or personal rapid transit, does not currently exist. In such circumstances, Stated Intentions (SI) data might be used – where respondents are naively asked whether they intend to sue a new public transport facility. However, as might be expected such an approach is vulnerable to policy response and non-commitment biases and will lead to over estimates of usage (Couture and Dooley, 1981). An alternative is provided by more sophisticated hypothetical data approaches which have become known as Stated Preference (SP) techniques. Some of the earliest applications were in studies of British rail demand (Sheldon and Steer, 1982), with a more recent application given by Hensher and Rose (2007). These techniques have been particularly helpful in comparing the relative attractiveness of intermediate public transport modes such as high frequency busways and light rapid transit (Ben-Akiva and Morikawa, 2002). More recent developments have included the use of more sophisticated models using techniques such as mixed logit (Greene et al., 2006) and by combining revealed and stated preference data (Polydoropoulou and Ben-Akiva, 2001). Application of these disaggregate models can be data intensive and they are often applied with aggregate data using incremental formulations of the nested logit (Bates et al., 1987).

Choice models have been used to forecast the usage of the Channel Tunnel related rail services and to forecast the usage of HS2, where two rival models have been developed – PLANET Long Distance and the Long Distance Model – see Fox et al. (2012). An issue seems to be the over forecasting of minority flows. The forecasts of the shares that rail has obtained of the inter-capital market have been broadly accurate. There were, however, gross over-forecasts of the traffic between areas beyond London to areas beyond Paris. This was only partially due to the failure to provide through services north of London (see, for example, National Audit Office, 2001, 2012) and seems also to relate to the difficulty in forecasting zero flows. Small flows summed over a large number of origin and destination can lead to substantive demand which in practice does not materialise.

<A>10.4 NETWORK MODELS

Where there are substantive public transport networks, a different demand modelling approach has developed based on assignment (route choice models). For example, the kernel of the PLANET long distance model referred to above is an EMME/2 based rail assignment model. The problems in modelling public transport networks are concisely stated by Ortuzar and Willumsen (2011, 373‒380). Compared with private transport modelling, issues in public transport include the need to incorporate the capacity of vehicles as well as routes, to include on-street (usually bus) and off-street (usually rail) routes, to estimate wait time (both at the public transport stop/terminal and at other locations), to include walk time and transfer time and to consider ticket types and prices. The outcome of these issues is the so-called common lines problem. For many origin and destination pairs there will be a large number of feasible public transport routes. In the context of long distance public transport, Jansson et al. (2005) discuss the example of travel between Gävle and Malmö in which 42 acceptable travel paths were identified.

Developments in this form of public transport modelling are given by Voss and Daduna (2001), Lam and Bell (2003), Ceder (2007), Desaulniers and Hickman (2007) and Guihaire and Hao (2008). Using operations research techniques these approaches offer the prospect of optimising the networks to achieve certain objectives such as maximising net social benefit subject to a budget constraint, although more usually this is based on minimising journey times subject to capacity constraints.

Initial emphasis was placed on frequency based assignment models based on mathematical programming techniques. Two examples of such models include the EMME/2 model based on the work of Spiess and Florian (1989) (and referred to above) and the VIPS model based on the Random Departure Time (RDT) algorithms of Hasselstrom (1981). In practice, these assignments may retain features of the deterministic all or nothing approach, whilst Bates and Preston (2011) report that the EMME/2 assignment results can be sensitive to coding conventions, so that, for example, new public transport stops (and routes) can have a disproportionate impact. This seemed to contribute to problems in modelling station choice and access to HS2 in London. Subsequent developments to overcome these types of problems are summarised in Ceder (2001, 2003), Florian (2003) and de Cea and Fernandez (2008).

More recently, emphasis has been placed on dynamic schedule-based assignment, typified by the DY-RT model applied to regional transport systems in the Lazio and Veneto regions of Italy (Nuzzolo et al., 2000) and the DY-BUS model developed for Salerno (Nuzzolo et al., 2001; see also Nuzzolo, 2003). Other examples include the PRAISE model, applied to rail markets in Britain and Sweden, and the QBM model, applied to bus markets in Britain – although these are choice models applied at a route level (Preston, 2008). As Jansson et al. (2008 ) stress a weakness of these approaches is the over-reliance on multinomial logit choice models, as the independence of irrelevant alternatives axiom is problematic in destination and route choice contexts. More advanced model formulations such as the cross nested logit model (Cascetta and Papola, 2003) get over some aspects of this problem but require detailed information on ideal departure (or arrival) times.

In the UK, at least, the practice of network planning is lagging somewhat behind the theory, with a continued reliance on manual or semi-automated approaches, based on elasticity models (essentially the approach adopted by Transport for London and by the Association of Train Operating Companies). Computer based public transport network planning is largely limited to one-off applications of frequency based assignment models such as EMME/2, VIPS (now incorporated into VISUM) and TRIPS (now CUBE). Practical examples include the PLANET model of the commuter rail network in London and the South East and Transport for London’s Railplan model (which despite its name includes all forms of public transport).5

<A>10.5 CONCLUSIONS

We have seen that a range of techniques have been used to analyse public transport markets. The choice of technique will often involve a trade-off between model accuracy and model cost. Following Alonso (1968), this in turn can be related to specification error (which may be expected to decrease with model complexity and hence cost) and measurement error (which may be expected to increase with model complexity). This is illustrated for forecasting the demand for new local railway stations by Figure 10.2.

[Figure 10.2 about here]

For this application context, namely new local rail stations in Britain, it was found that the most accurate results were given by the aggregate simultaneous model, which is akin to the direct demand models discussed in section 10.3 and models that underpin the elasticities described in section 10.2. Moreover such models could be calibrated and validated at relatively modest cost (assuming appropriate secondary data sources are available). Although one must be careful in generalising from a specific set of results, this does seem to vindicate the approach taken to modelling public transport demand in practice, with an emphasis on elasticity and direct demand models (which in any event are inter-related), applied at the route level. The one important caveat is that such an approach fails to view public transport as a network, and where network benefits are important to consumers this could be a serious omission.

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<A>NOTES

1. Source: Transport Statistics Great Britain 2013, Table NTS0409 (TSGB0104), retrieved from https://www.gov.uk/government/publications/transport-statistics-great-britain-2013, accessed 7 October 2014.

2. Ibid., Table TSGB0106.

3. Elasticities Database Online at http:/ /www.bitre.gov.au/tedb, accessed 7 October 2014.

4. Transit elasticities and cross-elasticities at http:/ /www.vtpi.org/tranelas.pdf, accessed 7 October 2014.

5. See *Local Transport Today*, **567**, 25 March 2011. Retrieved from https://transportxtra.com/magazines/local\_transport\_today/news/?ID=26107, accessed 7 October 2014.

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