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TECHNICAL REPORT

Manchester Motorway Box

Post-Survey Research of Induced Traffic Effects

Model Estimation

James Fox, Andrew Daly

RAND EUROPE

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Prepared for the UK Department for Transport

RAND EUROPE

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Preface

RAND Europe, in conjunction with Mott MacDonald and Denvil Coombe, has been commissioned by the UK Department for Transport to conduct research to measure the induced traffic effects resulting from the completion of the Manchester Motorway Box (MMB). This project is a culmination of earlier research undertaken by MVA to assess the feasibility of identifying induced traffic effects, and to plan and undertake the necessary data collection.

RAND Europe is the lead partner for this study and is responsible for the modelling and analysis used in the study. Mott MacDonald is responsible for provision of data inputs for the modelling and analysis, including population, employment and car ownership data, and the development of highway and public transport networks and trip matrices. Denvil Coombe provided quality assurance and modelling advice throughout the project, providing detailed review of the processes for development of the highway and public transport networks and matrices (and the reports of this work), as well as reviewing intermediate outputs from the demand modelling work.

This report documents the estimation of the travel demand model. It is a highly technical report that will be of use to modellers who are interested in the detailed specification of the models developed for this study. The work reported here has been undertaken by RAND Europe.

Four other reports have already been produced for this study:

a) an inception report that set out the proposed analysis and modelling approach for the study;

b) a report by Mott MacDonald outlining the validation of the highway and public transport networks, and the trip matrix estimation procedures and validation findings;

c) a report by Mott MacDonald describing the development of the land-use data before (1999) and after (2003) the completion of the MMB.

d) A report by RAND Europe summarising the main findings from each component of the study.

The final deliverable for this study will be a summary report, discussing key findings, in terms of what has been learned from the development of the highway and public transport networks, from the development of the travel demand model, and from the analysis of the induced effects as a result of the completion of the Manchester Motorway Box scheme.

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Summary

Background

The 1994 report of the Standing Advisory Committee on Trunk Road Assessment (SACTRA) concluded that **induced traffic**, that is traffic that is induced because of the provision of transport infrastructure, could have important implications on appraisal of the benefits of new roads for some time:

"*…the economic value of a scheme can be overestimated by the omission of even a small amount of induced traffic. We consider this matter of profound importance to the value-for-money assessment of the road programme*" (SACTRA 1994).

This same report recommended that the Department for Transport's research programme be expanded to include in-depth before and after monitoring of schemes. This recommendation was accepted by the Department and a commitment was given to undertake an expanded programme of research, including consideration of a Before and After study of the completion of the Manchester Motorway Box. At that time, the completion of the M60 box around Manchester was the largest planned scheme in the UK for which a programme of Before and After surveys could be conceived and it was argued that, although atypical of the general scale of road schemes, its large scale would maximise the changes of detecting and quantifying induced traffic effects.

A comprehensive programme data collection of intercept-surveys with road and public transport travellers, across specified screenlines was undertaken Before and After the completion of the motorway box. In the same period, but not as part of the study, household and roadside interviews for the Greater Manchester Area Transport Study (GMATS) were undertaken.

Overview of the Study

This study set out to quantify changes to travellers' choice of mode, where they travelled to (their destination), when they chose to travel (departure time) and the probability that they made a journey, as a result of the completion of the Manchester Motorway Box. Measuring these impacts, however, is complex: because many of the responses may occur simultaneously; because the size of impact will vary for different people, depending on where they live and where they want to travel; and, because the additional capacity itself is limited. So, although data that has been collected can (and has) been used to provide an estimate of the total change in traffic levels as a result of the introduction of the Scheme, a model is required to be able to disentangle the different traveller responses. To maximise the efficiency of the modelling and to give the best chance of identifying and separating

out the changes in repose due to the different behavioural mechanisms, the models were developed using fully disaggregate data and using discrete choice methods, using all available data (both the intercept surveys, collected specifically for the study, and household surveys collected at the time).

The importance of the different traveller responses were measured in two ways: (i) the primary aim of the study as defined by the Department for Transport, was to examine the relative magnitudes of these different effects *in a parametric form*, that is to gauge the importance of different impacts from the structure of the model, and (ii) a secondary aim was to distinguish the induced effects arising from the Manchester Motorway Box scheme from other changes that may have occurred.

This report focussed on the development of models to address the first of these aims. The separate summary report produced for this study (TR-840-DFT) discusses the second of these aims.

Estimation Summary

Chapter 11 provides a comprehensive summary of the findings from the model estimations. This summary discusses the key findings.

Models were developed from before (1999) and after (2003) intercept surveys, road side interview data collected from car drivers, and en-route public transport interview surveys. Models were estimated separately by dataset, and by pooling the two datasets.

The model results demonstrated that is was possible to model destination choice from these datasets, but pooling the road side interview and public transport interview data did not support the estimation of mode choice models. Time period choice could only be modelled using the public transport data. Finally, there was little evidence for longitudinal effects, that is to say changes in sensitivity between the before and after cases.

Household interview models were developed for five home-based purposes, using 2002 household interview data collected after the M60 was completed. In contrast to the intercept models, a substantial number of socio-economic effects were identified in the household interview models, in particular terms relating to car availability.

The structural tests investigated the relative sensitivity of mode, destination and time period choices. For mandatory purposes (commute, business and education) these tests concluded that the household interview data provides little data on (macro) time period choice, and so time period choice should be dropped from the structure, and that a structure with modes above destinations gives the best fit to the data. For discretionary purposes (shopping, other) the optimum structure had modes and time periods above destinations. However, the evidence for this finding is not strong.

The final stage in model estimation was to estimate pooled models from both the intercept surveys and the household interview data, with the intercept data used to model destination choice only. The household interview data was used to model mode and destination choice for mandatory purposes, and mode, time period and destination choice for discretionary purposes.

The structural tests for mandatory purposes confirmed the findings from the household interview models, with modes above destinations in each case. The structural test for shopping was also consistent with the household interview tests, with modes above destinations above time periods. However, it was not possible to identify a plausible structure for other travel, and thus a multinomial structure was adopted for the final model specification.

The pooled models were validated by examining the implied values of time (VOTs), comparing observed and predicted tour length distributions, and examining the model elasticities.

The commute VOTs are slightly low compared to the values in WebTAG. The business VOTs are substantially higher, but not as high as the employer's valuations given in WebTAG. For shopping and education, the VOTs are consistent with WebTAG. Finally, for other travel the car VOTs are slightly low, and the public transport VOTs slight high, compared to WebTAG.

The comparison of observed and predicted tour length distributions for car demonstrated an excelled match for all purposes except business, where short tours are underpredicted. For public transport, the match is excellent for commute, and good for other purposes, with a tendency to under-predict short tours.

The fuel cost elasticities were judged to be reasonable in the final models, with the lowest value for business as would be expected. The car time elasticities were also judged to be reasonable.

Acknowledgements

It would have not been possible for us to complete this study without our study collaborators, Dr Tom van Vuren and Paul Hoad, from Mott MacDonald, who provided the network data, essential for the development of the models; and Dr Denvil Coombe, who provided continued and valued advice throughout the project. We also wish to acknowledge the contribution of John Bates, who acted as an advisor to the study for the Department for Transport, and whose inputs have improved the resulting models and reports. Also, we thank Charlene Rohr for valuable comments on an early draft of this report, and Peter Burge for his useful comments on the final draft. In addition to the authors listed, Charlene Rohr, Stephen Miller, Ala'a Shehabi, Aruna Sivakumar and Bhanu Patruni all made valuable contributions to the analysis documented in this report. Finally, we would like to thank Geoff Hyman, the project officer from the Department for Transport, for his interest, constructive comment and commitment throughout the project. However, RAND Europe retains responsibility for any errors or misrepresentations contained in the report.

CHAPTER 1 Introduction

1.1 Background to the Study

Until 1994, when the Standing Advisory Committee on Trunk Road Assessment (SACTRA) published 'Trunk Roads and the Generation of Traffic', the UK Department for Transport's traffic and economic appraisal methods used for trunk road schemes assumed that, in most cases, reassignment (i.e. making the same journey by a different route) was the only significant impact on trip-making behaviour resulting from trunk road investment. The Department accepted SACTRA's advice that this assumption could no longer be supported and that, both in the short and longer term, there is a wider range of responses in addition to traffic reassignment. While the extent of these responses is unclear, theory suggests that, in some circumstances, they could have a significant impact on the economic benefits of schemes. These responses (collectively referred to as *induced traffic* effects) include: rescheduling of trips to take advantage of improved conditions at peak periods; increasing frequency of trips; decreasing vehicle occupancy; switching between public transport and private vehicles (mode shift); travelling to new destinations; making entirely new vehicle trips and changes in the patterns of land use or car ownership.

SACTRA recommended that the Department's research programme be expanded to include in-depth before and after monitoring of schemes. Its recommendation was accepted by the Department and a commitment was given to undertake an expanded programme of research, including consideration of a before and after study of the completion of the Manchester Motorway Box (MMB), which is the M60 orbital motorway around Manchester.

The MMB scheme is one of the last major contributions to the UK national road system. The scheme which completes the Manchester Motorway Box, is a section of dual four-lane carriageway, about 9 km in length. This was the largest scheme at the time for which a programme of before and after surveys could be conceived and it was argued that, although atypical of the general scale of road schemes, its large scale would maximise the chances of detecting and quantifying the induced traffic effects.

In 1997, a feasibility study was conducted for the Department by MVA. This study concluded that successful results could be obtained for the responses relating to trip frequency, trip distribution, mode choice and trip retiming. The feasibility study also indicated that these results could be obtained at an acceptable cost, provided that an appropriate survey strategy was adopted.

The Department then commissioned a planning study from MVA, which investigated the area most likely to be affected by the completion of the Manchester Motorway Box and, consequently, the most cost-effective data collection strategies for the before surveys. The MVA study recommended that data should be collected through roadside interviews in which a sample of drivers would be stopped and questioned. Alternative roadside interview strategies relating to the selection and proposed sampling rates of different sites were investigated and recommendations made. Appropriate public transport (PT) user surveys were also planned. Having identified satisfactory survey options, the planning study developed a comprehensive survey plan involving field visits to screenlines, production of site sketches, discussions with the police and highway authorities, and specification of the count programme.

The before surveys were commissioned by the Department from the Greater Manchester Transportation Unit (GMTU) and took place during the latter part of 1999 and early 2000. These surveys included roadside interviews, bus passenger surveys, Metrolink passenger surveys, and car and bus journey time surveys, each with an associated programme of traffic counts. The resulting data were checked, cleaned, expanded and delivered to the Department and have been used in a number of studies in the Manchester area.

Subsequently the Department commissioned the after surveys, which were conducted towards the end of 2003 and in early 2004. Data from these were treated similarly and delivered to the Department.

During the before and after survey period, GMTU also undertook a programme of household and roadside interviews for the Greater Manchester Area Transportation Study (GMATS), although household interviews were only collected during the after survey period. It should be noted that these data were not originally conceived as part of the study and were collected by GMTU for other reasons.

1.2 Overview of the Present Study

The main objective of the current study, as specified in the project brief, is:

> *'….to measure the magnitudes of … mode choice, destination choice, trip retiming, etc.… in a parametric form, that can be used for the construction of a detailed (market segmented) travel demand model. A secondary aim is to distinguish the induced effects that arise from the scheme from other changes that may have occurred.'*

We considered a number of possible behavioural responses that might result from the completion of the MMB (referred to as 'the scheme' throughout this report):

- **land-use impacts** – specifically those that have been generated by the scheme;
- **car ownership** – reflecting car ownership changes that can be directly attributable to the scheme;
- **public transport pass ownership** – reflecting PT pass ownership changes that can be directly attributable to the scheme;
- **travel frequency** – representing changes in numbers of trips as a consequence of the scheme;
- changes in **destination choice**;
- changes in **mode choice**;

- **car occupancy changes**;
- **(macro) changes in departure time** – through rescheduling of activities;
- **peak spreading** – through smaller (micro) changes in departure time;
- changes in **route choice**.

Following consideration of the data sources and resources available for this study, we decided not to model explicitly some of these responses.

Land-use impacts that are induced by the scheme were not predicted, on the basis that the time between the before (1999–2000) and after (2003–2004) situations is relatively short and the costs of building a land-use and transport interaction model are substantial, given that land-use data were not collected as part of this study. We treated observed land-use changes, including changes in population, employment, school enrolments, retail activity, etc. as *inputs* for the model forecasts.

We did not model the impacts of the scheme on car ownership either, on the basis that it was not possible to develop local car ownership models from the only suitable existing local data, specifically the GMATS household interview (HI), because no income information was collected in that survey. Additionally, any response in public transport pass ownership was expected to be small; the costs for developing such a model were not justifiable.

Highway and public transport assignments represented route choice effects; in the case of public transport, the assignment also represented PT sub-mode choice.

Following these decisions, the demand model therefore takes into account changes in travel frequency, destination, mode and macro time period choice (four time periods).

1.3 Contents of this Report

In this report we describe the estimation of choice models of travel frequency, mode, destination and time period. We developed these models to enable the construction of a detailed (market segmented) travel demand model that seeks to distinguish the induced traffic effects resulting from the completion of the M60 Manchester Motorway Box (MMB) scheme from other changes that have occurred.

The inception report set out the proposed analysis approach for this study. Two more reports have been produced describing key inputs to the modelling process:

- the validation of the before (1999) and after (2003) highway and public transport networks, and the trip matrix estimation procedures and validation findings;
- the development of before and after land-use data.

The application of the travel demand models to forecast demand for the MMB, and to analyse the induced traffic effects, will be documented later in the summary report.

In Chapter 2, we start by setting out key features of the estimation approach that we followed. Next, we present the scope of the models, with a list of the purposes modelled, and descriptions of the mode, destination and time periods represented. Finally, we describe the plan for model estimation.

Chapter 3 sets out the data used in model estimation. We describe the two sets of intercept data collected in the before and after surveys, namely the roadside and public transport interviews, and we also document the after HI data. The level-of-service data used in model estimation are briefly outlined (we provide a full description in the separate level-of-service report) (Mott MacDonald, 2008a). We describe the car cost data, together and discuss how costs are adjusted to account for inflation and income growth. Finally we briefly outline the land-use data; again there is a full description in a separate report (Mott MacDonald, 2008b).

In Chapter 4 we show how we developed models to explain mode, destination and time period choice from the intercept and HI datasets. The chapter sets out the model alternatives, the conditions used to determine their availability, and the utility functions used to describe their attractiveness. Finally, we describe the structural tests used to assess the relative sensitivity of different choice decisions, and the longitudinal tests run to test for the relative importance of cross-sectional and longitudinal effects.

Chapter 5 presents results for the intercept models, with results presented for separate roadside interview and public transport models, as well as models that pool the two intercept datasets.

Chapter 6 presents the results from the household interview model.

Chapter 7 presents the results from the pooled intercept and household interview models, which represent the final models of mode, destination and time period choice.

Chapter 8 presents validation of the pooled models presented in Chapter 7.

Chapter 9 documents the frequency models, which we developed to predict the number of tours as a function of the population by socio-economic segment and accessibility. Accessibility is measured using a ‘logsum’ from the models of mode-destination-time period choice described in Chapter 8.

Chapter 10 documents the freight models that we developed for light-goods-vehicle and other-goods-vehicle vehicle types, and which represent destination and time period choice.

Finally, Chapter 11 summarises the main findings from the model estimation work.

The wider findings of this study are documented separately in the summary report produced for this study (Rohr *et al,* 2010).

CHAPTER 2 Estimation Overview

Section 2.1 sets out the key features of the modelling approach we adopted for this study. Section 2.2 sets out the scope of the models in terms of the travel purposes represented, the modes modelled, and the destination alternatives represented. Finally, Section 2.3 describes the plan we followed to estimate the models, taking into consideration the complex nature of the models and the large choice datasets.

2.1 Modelling Approach

It is useful at this stage to summarise some key features of the modelling approach that we adopted for this study.

First, the models that we developed are disaggregate in nature, that is to say they are estimated from individual choice records of tours or trips, rather than from matrix level information. Disaggregate approaches make use of all the variance present in the data and can take advantage of discrete choice methods that are statistically efficient. A particular advantage of the disaggregate approach in the context of this study is that some of the induced components were expected to be small, despite the large database, and a modelling approach that makes full use of the variance in the data is more likely to detect small effects. A full discussion of the choice of modelling approach set in the context of the scoping study for this work is provided in Appendix A.

Second, the modelling approach uses all of the available choice data simultaneously. The choice data comprise both before (1999) and after (2003) intercept surveys collected specifically for this study, and household interviews collected in the after (2002) situation for different purposes, but which nonetheless proved extremely useful.[1] An important consideration when combining these datasets is differences in trip length distributions; specifically, intercept surveys survey more long-distance trips – most short-distance trips do not cross screenlines. To account for these differences in a statistically robust manner we used a weighting procedure, described in Appendix B.

Third, the pooled models represent three of the choice responses – mode, destination and time-of-day – simultaneously, an approach that ensures consistent treatment of cost and time in each model component; introduces more variation in the cost and time terms, maximising statistical efficiency; and enables different model hierarchies to be tested.

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1 Chapter 3 summaries the choice data available for model estimation.

One concern raised about the approach of pooling before and after data was that cross-sectional variation may dominate over longitudinal variation; this dominance would be at odds with the aims of the study in respect of identifying and predicting temporal changes. To address this concern we made a special test to distinguish cross-sectional and longitudinal effects, described in Section 4.6.

In addition to the mode-destination-time period models that form the main focus of this report, we also developed frequency and freight distribution models. The frequency models were developed from the HI data alone, as the intercept data were not suited to the development of disaggregate frequency models, whereas the freight distribution models were developed from the roadside interview data.

2.2 Model Scope

Following the discussion in Section 1.2, the choice models for this study are confined to predicting frequency, destination choice, mode choice and macro-time period choice.

As noted in Section 2.1, we estimated models for three of the response mechanisms – mode, destination and time of day choice – simultaneously. It was not possible to estimate the frequency choice within the same structure, and so models of travel frequency were modelled separately.

The models of mode, destination and time period choice formed the core of the modelling effort and are the main focus of this report. In general, references to the 'models' indicate these three; we discuss the frequency models separately in Chapter 10.

2.2.1 Modelling Unit

The modelling unit for home-based (passenger) travel in the travel demand model is a full *tour,* which is a series of linked journeys starting and finishing at the same home location. Some half-tours are observed in the HI, ie chains of trips that start outside the home and return there, or chains of trip that leave home but do not return. However, half-tours form a low percentage of the data and are not modelled.

Is should be noted that the intercept data surveys trips, not tours, and indeed we originally envisaged undertaking the modelling using trips alone; the decision to use tours results from our decision to use the HI data. The advantages of modelling using tours, not trips, are as follows:

- Tour based approaches model the choice of mode and destination choice as a function of network conditions on both the outward *and* return legs of the tour, whereas trip based approaches model each leg independently.
- Tour based approaches model the choice of mode for the entire tour, e.g. if an individual drives to work they are highly likely to drive home again. Because trip based approaches model each leg independently, the relationship between outward and return leg modes is ignored.
- Similarly, tour based approaches model the choice of destination for the entire tour, i.e. the outward leg arrives at the same location that the return leg originates from. This linkage is not present in trip based approaches.

- Non-home-based travel can be related to the (home-based) travel which occurs before and after in a tour based approach. By contrast, in a trip based approach non-home-based trips are forecast independently of home-based travel, which is less realistic.
- Tour based approaches are embedded in an activity based framework, i.e. they reflect the fact that travel is a derived demand, driven by the need for activity participation. The link to activities is much less clear in the trip based approach.

To model home-based trips from the intercept data within a tour-based framework required procedures to determine the level-of-service for the unsampled leg. These procedures are described in Section 4.4.1.

To model non-home-based (passenger) travel and freight, we use trips, not tours.

2.2.2 Purposes

Five home-based tour purposes were distinguished in the passenger models:

- home–work
- home–business
- home-education
- home–shopping
- home–other

Two non-home-based (NHB) trip purposes were modelled:

- NHB business
- NHB other

NHB travel was modelled as individual trips.

To model freight travel, we segmented trips into Light Goods Vehicles (LGVs) and Other Goods Vehicles (OGVs).

2.2.3 Modes

Five modes were distinguished in the models:

- car driver
- car passenger
- public transport
- cycle
- walk

We modelled car driver and car passenger modes separately so that the impact of the MMB scheme on occupancy could be assessed. Public transport was treated as a single mode in the demand model, with sub-mode choice between train, Metrolink and bus handled in the PT assignment. This decision was explained in Section 3.3.1 of the Inception Report (RAND Europe *et al*, 2005).

Cycle and walk modes were only modelled using the HI data, as no information on these models was collected in the intercept surveys.

2.2.4 Destination Alternatives

The destination alternatives comprise the 559 zones used in the sub-regional highway model (SRHM) by GMTU and cover Greater Manchester and its surrounding area.

We estimated destination constants in the modelling to balance trips at the district level, with the following districts represented:

- Manchester
- Trafford
- Salford
- Wigan
- Bolton
- Bury
- Rochdale
- Oldham
- Tameside
- Stockport
- Wilmslow
- Glossop
- Poynton
- external zones

2.2.5 Time Periods

Four macro time periods were distinguished in the models:

1. AM peak 08:00 to 09:00
2. PM peak 16:00 to 18:00
3. inter-peak 07:00 to 08:00, 09:00 to 16:00, 18:00 to 20:00
4. off-peak 0:00 to 07:00 and 20:00 to 24:00

The definition of the inter-peak is unusual in that it covers shoulder periods before the AM-peak and after the PM-peak, as well as the period between the peaks. The decision to define the inter-peak in this way was based on plots of flow volume against time of day, which demonstrated that flow volumes in the shoulder periods were similar to flows in the period between the two peaks.

2.3 Estimation Plan

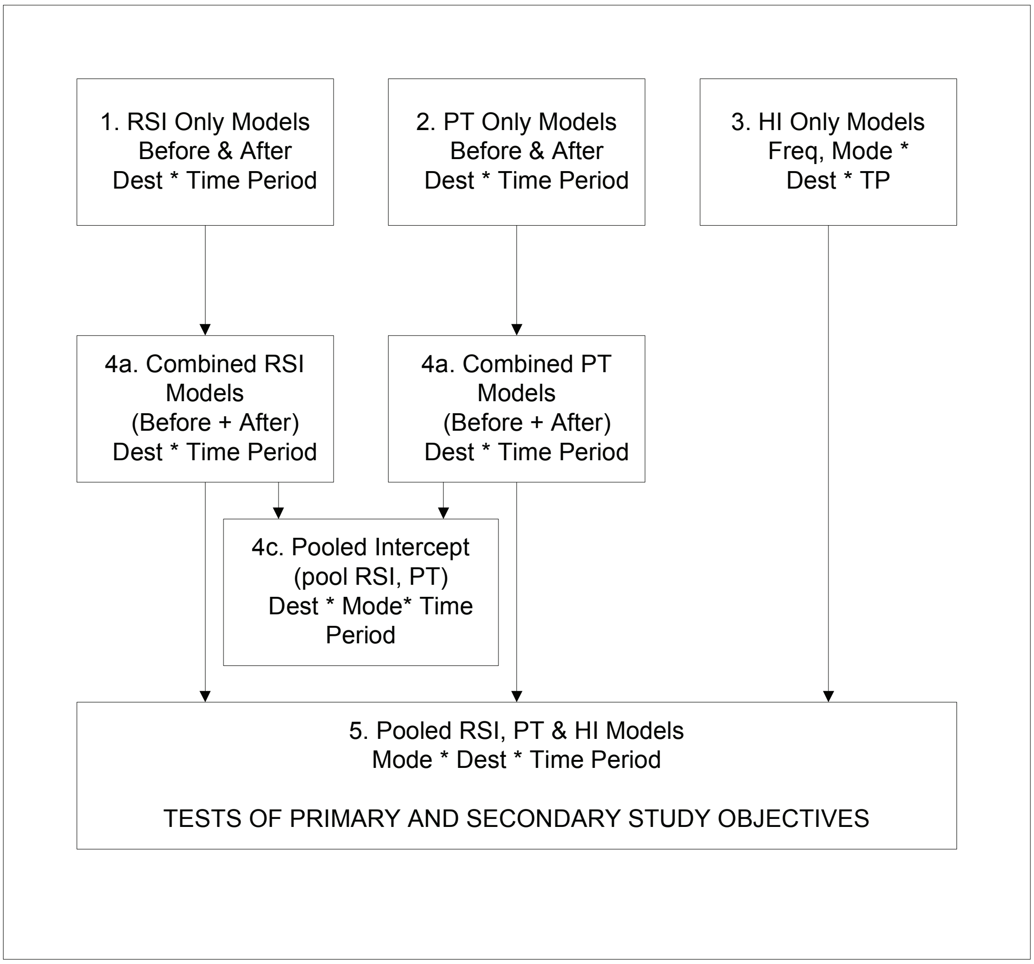
We developed complex final models in this study, combining data from roadside, public transport and household interviews. The run times for these combined models are correspondingly high, and so resolving problems with these models is time consuming. To develop the models as efficiently as possible, we devised a model estimation plan that first developed simple models separately for each dataset; only once problems with these separate models had been resolved were the datasets pooled together.

Models were developed first for the commuting purpose following a five-step plan:

1. RSI models, separately for before and after – destination *x* time period.
2. PT interview models, separately for before and after – destination *x* time period.
3. Household interview models (after only) – frequency, and mode *x* destination *x* time period.
4. Combined before and after intercept models, with three sets of models run:
    a. Combined RSI models – destination *x* time period
    b. Combined PT models – destination *x* time period
    c. Pooled RSI and PT models – destination *x* mode *x* time period
5. Pooled intercept and household interview models – mode *x* destination *x* time period

The following figure illustrates this step-wise process of model development.

Figure 1: Model Development Steps



Note that step 4c., combining the RSI and PT datasets with model mode, destination and time period choice, was not successful, which is why there is no link from that step to box 5 in this figure.

For purposes other than commuting it was only necessary to run steps 3, 4 and 5.

CHAPTER 3 Estimation Data

The following data are required to estimate the choice models:

- choice data, namely the tours and trips observed in the intercept and HI datasets on weekdays, documented in Sections 3.1 and 3.2 respectively
- level-of-service data to link to the choice data, documented briefly in Section 3.3, and in full in Mott MacDonald *et al* (2008a)
- cost data to link to choice and level-of-service data, documented in Section 3.4
- land-use data to represent the attractiveness of destination alternatives, documented briefly in Section 3.5 and in full in Mott MacDonald *et al* (2008b).

In all four cases these data are required for both the before (1999) and after (2003) cases.

3.1 Intercept Data

3.1.1 Roadside Interview Data

GMTU supplied the before and after roadside interview (RSI) databases as Access databases. The majority of the before interviews were collected on weekdays in the Spring of 1999 (March, April, May) although some interviews were also collected in June, July and October of that year. The after interviews were collected during Spring 2003 (April to June). The data collection processes are documented in full in 'M60 before Study Technical Report 2' (GMTU, 1999) and 'M60 after Study Technical Report 2" (GMTU, 2004).

The data were then processed to append the SRHM zones corresponding to the postcodes of the trip origins and destinations. This processing was undertaken using the MapInfo GIS software.

We determined the purpose of car driver trips directly from the recorded origin and destination purposes. If the vehicle contained two or more occupants, passenger records were also generated. If the driver's purpose was escort, then the escort purpose was recorded in the data and the passenger's purpose could be determined directly. If the driver's purpose was not escort then we assumed that the passenger's purpose was the same as the driver's. In all cases we assumed that the passengers travelled to the same destination as the driver. Because of the number of assumptions that had to be made in the generation of passenger trips, we expected a higher level of error to be associated with passenger trips than to driver trips.

The total numbers of driver and passenger trips available for model estimation are summarised in the following tables. It is emphasised that the roadside interviews collected no socio-economic information.

Table 1: Road Side Interview Home-Based Trips

		Commute	Business	Education	Shopping	Other	Total
Before	Drivers	28,241	3,600	988	5,947	15,600	54,376
	Passengers	4,431	498	1,108	4,937	10,250	21,224
	Total	32,672	4,098	2,096	10,884	25,850	75,600
After	Drivers	37,776	4,025	1,555	9,993	19,561	72,910
	Passengers	4,530	464	1,437	7,289	9,897	23,617
	Total	42,306	4,489	2,992	17,282	29,458	96,527
Combined	Drivers	66,017	7,625	2,543	15,940	35,161	127,286
	Passengers	8,961	962	2,545	12,226	20,147	44,841
	Total	74,978	8,587	5,088	28,166	55,308	172,127

Table 2: Road Side Interview Non-Home-Based Trips

		Business	Other	Total
Before	Drivers	6,424	12,618	19,042
	Passengers	1,333	4,411	5,744
	Total	7,757	17,029	24,786
After	Drivers	5,963	14,647	20,610
	Passengers	1,016	5,381	6,397
	Total	6,979	20,028	27,007
Combined	Drivers	12,387	27,265	39,652
	Passengers	2,349	9,792	12,141
	Total	14,736	37,057	51,793

The volume of data available for model estimation is significant, with broadly comparable volumes of before and after data.

It is noteworthy that the volume of shopping trips intercepted is significantly higher in the after case. It is possible that more shopping trips are crossing the screenline as a result of completion of the scheme.

3.1.2 Public Transport Interview Data

GMTU supplied the before and after public transport interview (PTI) databases as Access databases. Separate databases were supplied for bus, Metrolink and rail surveys but the questionnaires were identical and so the databases were merged into before and after PT databases. The data collection process is documented in full in 'M60 before Study Technical Report 3' (GMTU, 1999) and 'M60 after Study Technical Report 3' (GMTU, 2004).

As per the RSI data, we then processed the data using GIS software to append the SHRM zones corresponding to the postcodes of the trip origins and destinations.

The numbers of home-based and non-home-based trips are summarised in the following tables.

Table 3: Public Transport Interview Home-Based Trips

	Commute	Business	Education	Shopping	Other	Total
Before	15,847	749	4,059	5,084	5,683	31,422
After	13,772	1,338	2,840	3,010	5,663	26,623
Combined	29,619	2,087	6,899	8,094	11,346	58,045

Table 4: Public Transport Interview Non-Home-Based Trips

	Business	Other	Total
Before	299	2,903	3,202
After	455	3,160	3,615
Combined	754	6,063	6,817

The volume of data is around one-fifth of the RSI total (11,300 trips compared to 55,308) but nonetheless there is still a significant volume of data.

It is interesting to note a substantial fall in the volume of shopping trips between the before and after cases, which together with the RSI figures in Table 1 and Table 2 suggests a substantial shift from public transport to car across the screenline. The number of trips for education also shows shifts from public transport to car, at least in the trip totals.

3.2 Household Interview Data

The household interview (HI) data were collected across Greater Manchester between January and March 2002. A total of 9,150 weekday household interviews were available for analysis.[2]

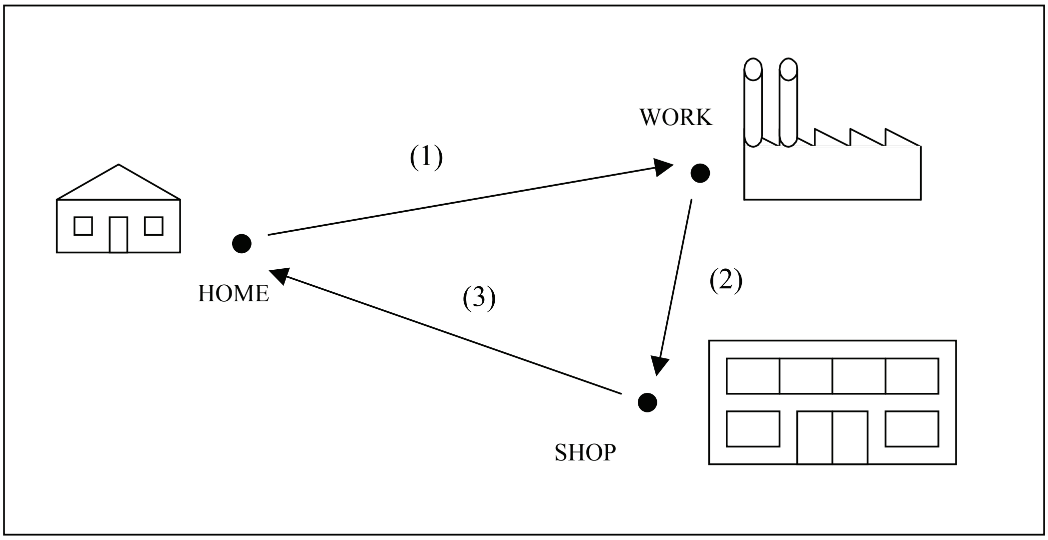
The HI data were supplied in Access format, with separate linked tables for household, person and trip information. In contrast to the intercept data, comprehensive survey documentation was not available to supplement the information in the database. From the material available it is clear interviewers were used to record the data, and that the surveys were one-day diaries. Before using the data in the modelling, we undertook a 'tour building' process to link the trip records into tours for modelling.

A tour is a series of linked trips starting and finishing at the home. If a traveller makes a simple return journey it is straightforward to determine the 'primary destination' of the tour, for example a home-work-home sequence of trips has work as the primary destination (PD) and so is a work tour. However, for complex sets of trips, it is necessary to define rules to identify the PD of the tour.

This problem is illustrated in Figure 2.

[2] Interviews were also collected over weekends but these were excluded from the analysis.

Figure 2: Tour Example



In this example a worker travels directly to work in the morning, but on the way home diverts to the shops. Rules are necessary to define the PD of the tour.

The PD can be determined by using the following purpose hierarchy:

- work;
- business;
- other purposes.

If there are ties, ie more than one destination on the same level in the purpose hierarchy is visited, the destination at which the most time was spent is taken as the PD. In the example given in Figure 2, work is higher in the hierarchy than shopping and so forms the PD. Therefore work is specified as the purpose of the tour, and the return trip between home and work is modelled. Trip (2) between the workplace and the shopping location would be modelled separately as a non-home-based trip.

The tour building process yielded the following numbers of home-based tours for model estimation.

Table 5: HI Home-Based Tours

Commute	3,827	23.5 %
Business	302	1.9 %
Education	2,597	15.9 %
Shopping	4,440	27.2 %
Other	5,153	31.6 %
Total	16,319	100.0 %

There are significant numbers of tours for all purposes except for business, where the share is expected to be low. However, the volume of data is substantially lower than that recorded in the intercept surveys.

3.3 Level-of-Service Data

Level-of-service data is needed for both the before (1999) and after (2003) scenarios in order to model the observed choices. We assumed that the 2003 after level-of-service data could be used to model travel observed in the HI data collected between January and March 2002.

The analysis we undertook to produce the highway level-of-service data is documented separately in the level-of-service report (Mott MacDonald, 2008a). In this section we describe only the level-of-service data available for the modelling. It should be noted that in the development of the level-of-service matrices, *observed* rather than modelled travel times from the before and after journey time surveys were used wherever available.

3.3.1 Highway Level-of-Service

For the four modelled time periods[3] the highway level-of-service provided information about:

- distance in km
- time in minutes.

The travel times are total travel times, there is no separation of free-flow time and time spent in queues. Level-of-service was not provided for intrazonal movements, and so was imputed using a procedure described in Section 4.4.1.

In addition, a special assignment was undertaken for each time period to determine screenline crossing rates. These assignments provided matrices that define the screenline crossing rates for each origin-destination pair. Note that values greater than one are possible, as there are two screenlines, and non-integer values are observed as multi-routing is possible.

3.3.2 Public Transport Level-of-Service

For the four modelled time periods the following information was available for use in the modelling:

- in-vehicle time in minutes
- walk access/egress time in minutes
- wait time in minutes
- number of boardings
- fare in pence.

There is no split between first and other wait times. Level-of-service was not provided for intrazonals.

As per highway, a special assignment was undertaken for each time period to determine screenline crossing rate matrices.

3 See Section 2.2.5.

3.4 Cost Data

The base year for the WebTAG car cost formulae is 2002, and the HI data were also collected in that year. Therefore all costs have been expressed in 2002 prices.

3.4.1 Car Costs

We calculated car costs using the procedure set out in WebTAG Unit 3.5.6, Section 1.3.1. In summary, fuel consumption is calculated as a cubic function of speed, which in our study we calculated on an origin-destination (OD) basis from the network distances and times – in many other studies global average speeds are used instead. We then calculated consumption from the network distance and an appropriate mean fuel cost, accounting for changes in the petrol-diesel split in the fleet over time.

Table 6 shows the fuel costs used.

Table 6: Mean Fuel Costs (2002 prices)

Year	Cost (p/litre)
1999	73.3
2002	75.2
2003	76.5

The 1999 figure is taken from Transport Statistics 2005, Table 3.3. The 2002 and 2003 figures are taken directly from WebTAG.

In line with WebTAG recommendations, we included non-fuel costs for business travel only. These were also calculated as per-kilometre costs, calculated as a function of speed, with speed, again calculated on an OD basis from network distances and times.

3.4.2 Parking Costs

We determined zonal parking costs from analysis of reported parking costs in the before and after RSI data. The analysis demonstrated significant differences between commuters and non-commuters in:

- the proportion of individuals paying for parking
- the prices paid for parking by those who do pay.

We therefore calculated average parking cost data separately for commuters and non-commuters. Using this segmentation, zonal parking costs for use in the modelling were calculated following a two-stage procedure for each zone:

- the proportion of people who pay for parking
- the mean parking cost of those who pay to park.

We used special procedures for zones with small samples.

- If there were fewer than ten observations in total for a zone, the average parking cost was taken to be zero for both commuters and non-commuters.
- If there were fewer than eight observations for one purpose, they were supplemented with the observations for the other purpose, weighted by a factor of one-half.

The after parking costs, collected in 2003, have been assumed to apply to the HI, collected in 2002. However they are adjusted back to 2002 prices, as we explain in the following section.

3.4.3 Inflation and Income Growth

To adjust costs to 2002 prices, we adjusted before (1999) and after (2003) costs to account for growth in consumer prices, using the CPI index. The following table presents the values we used and the CPI factors calculated from these values to convert to 2002 prices.

Table 7: CPI Indices (2005=100)

Year	CPI	CPI Factor
1999	92.3	1.035
2002	95.5	1.000
2003	96.7	0.988

As incomes grow in real terms over time, travellers' values-of-time (VOT) increase, and sensitivity to cost declines. Therefore in addition to the inflation adjustment, we made a further adjustment to the before and after costs to account for the impact of income growth on travellers' values-of-time. This adjustment is described in WebTAG consultation unit 3.12.2, Section 11.4. In order to implement the guidance, gross disposable household income (GDHI) per head figures for Greater Manchester were obtained from the National Statistics website.

Table 8: GDHI Per Head (£)

	1999	2002	2003
Current basic prices	9,428	10,708	11,064
2002 prices	9,729	10,708	10,865

A VOT factor was then calculated by applying an income elasticity to the income growth relative to 2002:

$$\boxed{\frac{VOT_{2002}}{VOT_y} = \left(\frac{I_{2002}}{I_y}\right)^{\eta}} \qquad (3.1)$$

where: VOT is the value-of-time

I is the mean income, taken from Table 8

η is the income elasticity (1.0 for business, 0.8 for all other purposes)

The VOT factor is applied to adjust costs to reflect 2002 values-of-time. The following values have been calculated.

Table 9: Values-of-Time Adjustment Factors

	1999	2002	2003
Business	1.1007	1.0000	0.9856
Other purposes	1.0798	1.0000	0.9884

In model estimation, all 1999 and 2003 costs are multiplied by the VOT factors as well as by the CPI factors given in Table 7. Thus the modelling takes into account both changes in real prices and income growth over time.

3.5 Land-Use Data

The creation of the land-use data is documented in full in a separate report produced as part of this study report (Mott MacDonald, 2008b). In the context of model estimation, the land-use data are only required to define the terms that represent the attractiveness of destination alternatives.

To specify these attraction terms, we produced separate files for the before and after cases, defining the following land-use data for each model zone:

- population
- total employment
- retail employment
- service employment
- education employment.

We used these files to specify the attraction variables used to measure the attractiveness of destination zones. It has been assumed that the attraction variables for the after case (2003) can be used to model the choices observed in the 2002 HI.

Table 10 details the attraction variables used for each travel purpose.

Table 10: Attraction Variables

Purpose	Attraction Variables
Commute	Total employment
Home-Business	Total employment
Home-Education	Education employment
Home-Shopping	Retail employment
Home-Other	Population Total employment Service employment
Non-Home-Based Business	Total employment
Non-Home-Based Other	Population Total employment Service employment
Freight, Light Goods Vehicles	Total employment
Freight, Other Goods Vehicles	Total employment

The selection of attraction variables is based on RAND Europe's observations from a number of modelling studies where simultaneous models of mode and destination choice have been estimated.

CHAPTER 4 Model Specification

The chapter begins with a description of the alternatives represented in the various models, after which Section 4.2 explains the conditions we used to specify the availability of these alternatives during the model estimation process.

Section 4.3 provides a definition of the utility functions we estimated to describe the attractiveness of the alternatives, and how we used these utility functions to calculate choice probabilities. It also explains how datasets have been scaled relative to one another to account for different levels of error between the different choice datasets.

Section 4.4 then describes the formulations we used for the key components of the utility functions, level-of-service terms, cost specification, car availability variables and other socio-economic terms.

4.1 Alternatives

The models we estimated are simultaneous models of joint destination and (in some cases) time period and mode choice.

4.1.1 Destinations

The destinations in the models are the 559 SRHM model zones. The rules used to specify destination availability are discussed further in Section 4.3.

4.1.2 Modes

For the roadside-interview (RSI) models, we made initial tests with both car driver and car passenger modes. However, as discussed in Section 5.1.2, passengers were subsequently dropped from the models and the final models include only car drivers.

For the public transport (PT) interview models a single PT mode is represented. As we noted earlier, we handled sub-mode choice (bus, metrolink or train) through the public transport assignment procedure.

For the household interview (HI) models all five passenger modes are available:

- car driver
- car passenger
- PT

- walk
- cycle.

4.1.3 Time Periods

Although there are four time periods, defined in Section 2.2.4, the off-peak was only partially interviewed in the intercept surveys and as a result it was not possible to define representative off-peak weights. Consequently we excluded the off-peak from the modelling of the intercept data.

The HI data provide information on tours and to model these it is necessary to define the combination of outward and return time periods. There are a total of 15 possible combinations detailed in Table 11. Note the unusual inter-peak definition, which straddles the peaks, allows for more combinations than would otherwise be expected.

Table 11: Time Period Combinations

	OP: 0-7	IP: 7-8	AM: 8-9	IP: 9-16	PM: 16-18	IP: 18-20	OP: 20-24
OP: 0-7	1: OO	2: OI	3: OA	2: OI	4: OP:	2: OI	1: OO
IP: 7-8		5: II	6: IA	5: II	7: IP	5: II	8: IO
AM: 8-9			9: AA	10: AI	11: AP	10: AI	12: AO
IP: 9-16				5: II	7: IP	5: II	8: IO
PM: 16-18					13: PP	14: PI	15: PO
IP: 18-20						5: II	8: IO
OP: 20-24							1: OO

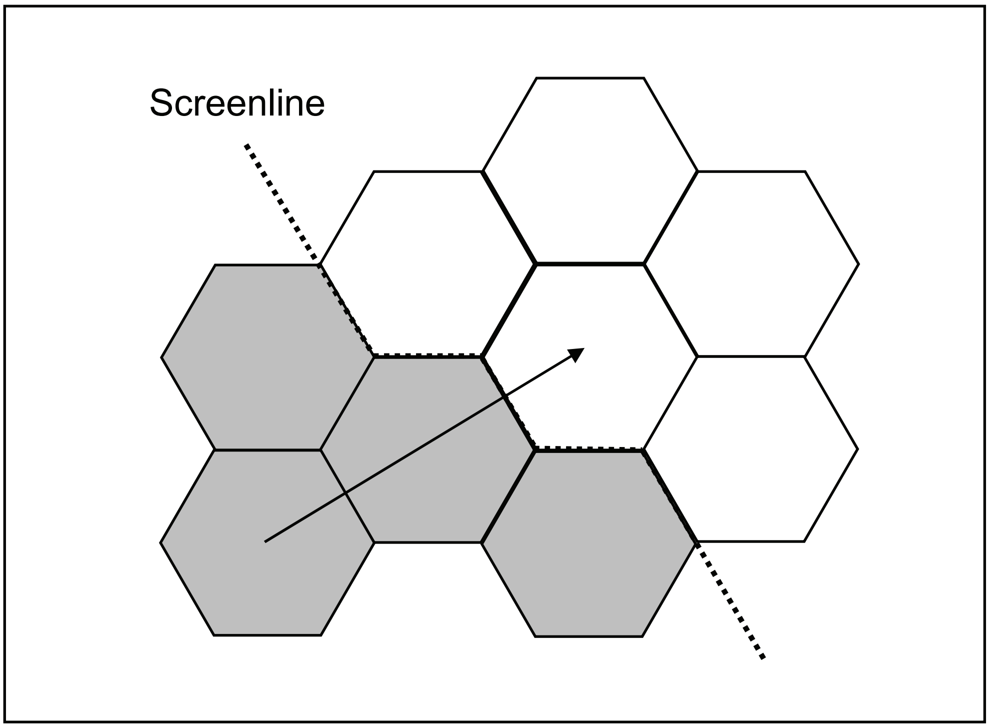
4.2 Availability

Different conditions are required to specify the availability of alternatives for the intercept models and the household interview models. These are described in the following sections.

4.2.1 Intercept Data

When modelling destination choice with intercept data it is necessary to take account of the fact that short-distance trips are rarely surveyed, as in most cases they do not cross a screenline. This is illustrated in Figure 3.

Figure 3: Screenline Availability



The observed trip is shown by the arrow, and is interviewed at the point at which it crosses the screenline. Zones shown in grey cannot be observed, because travelling to these zones would not have involved crossing a screenline.

To prevent the introduction of bias to the models, zones highlighted in grey in Figure 3 are set to be unavailable in the modelling, as they cannot be observed. To determine which zones are unavailable, we ran special assignments to determine the probability of crossing one or more screenlines. If the probability of crossing a screenline is below a certain threshold, the destination zone is set to be unavailable. Appendix B presents the results of analysis to determine the appropriate threshold probability.

In addition to the screenline availability check, zones have to have a non-zero attraction variable to be available. For purposes like commuting this means all destinations are available because there is employment in each zone; but for education, where the attraction variable is education employment, this condition does restrict the choice set.

When the RSI and PTI data are pooled, and mode choice is represented in the structure, the availability of the car driver alternative for PTI observations is specified using the car availability variable[4] collected within the PTI data.

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[4] The surveys record whether an individual had a car available for the trip made by PT.

4.2.2 Household Interview Data

In the HI data the probability of a trip being sampled is independent of the chosen destination. Therefore there is no need to use any screenline availability condition.

The availability of the five modes is specified as follows:

- car driver is available if the individual has a licence and the household owns at least one car
- car passenger is available to all individuals, as it possible to get a lift with people from outside the household
- public transport is available if there is a path between the origin and destination according to the assignment
- walk is available to all individuals
- cycle is available to all individuals.

Destination alternatives are available, provided that there is a non-zero attraction variable.

4.3 Utility Functions

We measured the attractiveness of each alternative by specifying a utility function, consisting of model parameters, referenced as βs. These β parameters comprise:

- alternative specific constants, which are always estimated relative to a base alternative
- terms multiplying level-of-service information such as travel times and monetary costs
- terms reflecting differences in preferences across socio-economic segments, in particular to explain mode choice.

The parameters are estimated by seeking to maximise the probabilities of the observed choices. This is achieved by maximising the log-likelihood function.

The initial model development was undertaken assuming a multinomial model structure, that is where destination, time period and mode (where represented) choices were at the same level in the hierarchy, which assumes each choice is equally sensitive to changes in utility.

The following sub-sections define the utility functions we developed for the RSI, PT and HI models respectively, together with probability expressions that illustrate how we used the utility functions to calculate the probability of choosing the model alternatives.

4.3.1 Road Side Interview Models

The utility of each destination-time period alternative for a given origin home zone is defined as follows:

$$\boxed{V_{d,tp} = \log(A_d) + \lambda\left(\beta_d + \beta_{tp} + \beta_{Cost}Cost_{d,tp} + \beta_{CarTime}Time_{d,tp}\right)} \qquad (4.1)$$

where: A_d is the attraction variable (total employment)

λ is the scale parameter 'CDbefore' (estimated relative to the after data), defined in Section 4.3.4

β_d is the destination constant, with Manchester specified as the base area

β_{tp} is the time period constant, with separate constants for outward and return trips, in both cases the AM-peak is the base

β_{Cost}, $\beta_{CarTime}$ are the level-of-service parameters estimated

$Cost_{d,tp}$ is calculated from WebTAG using time and distance skims, plus parking costs

$Time_{d,tp}$ is taken from the distance skims.

The probability of choosing a given alternative is then determined from the standard logit formula:

$$\boxed{\mathrm{P}_{d,tp} = \frac{\exp(V_{d,tp})}{\sum_{D}\sum_{TP}\exp(V_{d,tp})}} \qquad (4.2)$$

The probabilities $P_{d,tp}$ sum to unity over the 1,677 destination-time period alternatives (the number of alternatives is the product of 559 model zones and the 3 time periods represented).

4.3.2 Public Transport Interview Models

The utility for each destination-time period alternative for a given origin home zone is defined as follows:

$$\boxed{V_{d,tp} = \log(A_d) + \lambda \begin{pmatrix} \beta_d + \beta_{tp} + \beta_{Cost}Cost_{d,tp} + \beta_{PTTime}IVTime_{d,tp} \\ +\beta_{WtTime}WaitTime_{d,tp} + \beta_{WkTime}WalkTime_{d,tp} \\ +\beta_{Transfers}Transfers_{d,tp} \end{pmatrix}} \qquad (4.3)$$

where: A_d is the attraction variable (total employment)

λ is the scale parameter 'PTbefore' (estimated relative to the after data) , defined in Section 4.3.4

β_d is the destination constant

β_{tp} is the time period constant, with separate constants for outward and return trips

β_{Cost}, β_{PTTime}, β_{WtTime}, β_{WkTime}, $\beta_{Transfers}$ are the level-of-service parameters

$Cost_{d,tp}$, $IVTime_{d,tp}$, $WaitTime_{d,tp}$, $WalkTime_{d,tp}$, $Transfers_{d,tp}$ are taken from the PT skims.

The probability of choosing a given alternative is then determined from the standard logit formula:

$$\boxed{\mathrm{P}_{d,tp} = \frac{\exp(V_{d,tp})}{\sum_{D}\sum_{TP}\exp(V_{d,tp})}} \qquad (4.4)$$

The probabilities $P_{d,tp}$ sum to unity over the 1,677 destination-time period alternatives (the number of alternatives is the product of 559 model zones and the 3 time periods represented)..

4.3.3 Household Interview Models

The utility, or attractiveness, associated with each alternative is specified by a utility function v_{mdt} for the mode-destination-time period alternative mdt:

$$\boxed{\mathrm{v}_{mdt} = \beta_m + \beta_D + \beta_t + \sum_k \beta_k x_k} \qquad (4.5)$$

where: β_m is the mode-specific constant, with car driver the base mode

β_D is the district-specific constant for the destination, with Manchester specified as the base area

β_t is the time period-specific constant, relative to the AM peak-PM peak out-return combination

the term $\Sigma \beta_k x_k$ represents a sum of vectors

β_k is a vector of parameters to be estimated

x_k is a vector of observed data, which in the case of level-of-service data varies with alternative mdt.

The AM peak-PM peak combination is defined as the base combination as it is the most frequently chosen combination for a number of the model purposes (commute, business and education).

The terms $\Sigma\, \beta_k\, x_k$ vary according to the mode. They comprise level-of-service parameters and socio-economic parameters, which are set out in Section 4.4.

The probability of choosing a given alternative is then determined from the standard logit formula:

$$\boxed{\mathrm{P}_{m,d,tp} = \frac{\exp(V_{m,d,tp})}{\sum_M \sum_D \sum_{TP} \exp(V_{m,d,tp})}} \qquad (4.6)$$

The probabilities $P_{m,d,tp}$ sum to unity over the 41,925 mode-destination-time period alternatives (the number of alternatives is given by the number of possible combinations of 5 modes, 559 model zones, and 15 time period combinations).

4.3.4 Dataset Scaling

In the majority of intercept models, data from more than one survey is used. For models that combine before and after data from the roadside interview, we would expect similar levels of error in the models, on the basis that the survey forms and methodologies were similar in the two sets of interviews. However, sensitivities to changes in utility may vary between the before or after, or there might be a higher level of error in the before network data than the after.

In addition, when models are estimated from combinations of RSI, PT and household data, different levels of error would be expected between the different sets of surveys.

To account for these differences in error and/or sensitivity,[5] we added scale parameters to the models applied across a given dataset. We use the after data as the reference dataset, and the scale parameter λ set equal to one in equations (4.1) for RSI and (4.3) for PT. For the before data we estimate a scale parameter λ^B, which gives the level of error/sensitivity in the before data *relative* to the after data:

$$\boxed{\lambda^B = \frac{\sigma_A}{\sigma_B}} \tag{4.7}$$

where: σ_A, σ_B are the standard deviations in the before and after utilities respectively.

Thus a value of λ^B less than one indicates there is more error/less sensitivity in the before data relative to the after, whereas a value a value of λ^B greater than one indicates there is less error/greater sensitivity in the before data relative to the after.

When we pooled the intercept surveys to estimate models from both the RSI and PTI datasets, the after car driver data was set as the reference for the dataset scaling.

4.4 Utility Components

4.4.1 Level-of-Service Specification

The basic level-of-service (LOS) specification is specified in Table 12. The columns represent the modes, and the rows the various LOS data. The cell values then define the LOS parameters that enter the utility function for each mode.

Table 12: Household Interview Level-of-Service Specification

LOS Component	Car Driver	Car Passenger	Public Transport	Walk	Cycle
Driving Cost[6]	β_{Cost}	β_{Cost}			
Parking Cost	β_{Cost}	β_{Cost}			
PT Fare			β_{Cost}		
Car Time	$\beta_{CarTime}$	$\beta_{CarTime}$			
PT Time			$\beta_{PTIVTime}$		
Wait Time			$\beta_{WaitTime}$		
Walk Time			$\beta_{WalkTime}$		
Transfers			$\beta_{Transfers}$		
Distance		$\beta_{CarPDist}$		$\beta_{WalkDist}$	$\beta_{CycleDist}$

The allocation of car costs (driving plus parking) between drivers and passengers is made using a cost sharing formulation described in the following section.

Intrazonals require special consideration, as neither the highway nor PT skims provide LOS for them. Few intrazonal trips are observed for public transport, so we decided to set intrazonals as unavailable. However, for modes modelled using the highway LOS reasonable numbers of

5 Separating the two effects is not possible.

6 Note that driving cost is calculated from the LOS using formulae set out in WebTAG, rather than using driving cost skims from the network model.

intrazonal tours are observed, particularly for walk and cycle. Therefore we set intrazonals to be available for highway modes, and estimated an intrazonal dummy so that overall the observed share of intrazonal tours is matched by the model. In addition, mode-specific intrazonal dummies are added, estimated relative to car driver (the base mode), which ensure that the overall mode-specific intrazonal shares are reproduced.

LOS for highway intrazonals was calculated by taking half the LOS to the 'nearest' zone, where 'nearest' is defined by highway skim distance. The results of these tests are reported in Section 6.2.

4.4.2 Cost Formulations

Form of Cost Variable

There is substantial evidence of a cost damping effect, which we tested explicitly through the use of a logarithmic cost formulation. For the Manchester models, we assessed the relative importance of linear and log-cost more directly by testing models with both log and linear-cost terms, entered into the utilities as two separate terms.

When both linear and log-cost terms are present the implied values-of-time for each mode with a cost vary according to the cost of the tour, as shown by the following formula.

$$\boxed{VOT = \frac{\partial V / \partial Time}{\partial V / \partial Cost} = \frac{\beta_{Time}}{\beta_{Cost} + \frac{\beta_{LogCost}}{Cost}}} \qquad (4.8)$$

where: V is the utility function of the mode in question

β_{Time} is the in-vehicle time parameter for the mode in question

β_{Cost} is the linear cost parameter

$\beta_{LogCost}$ is the log cost parameter.

Allocating Car Costs

In the utility functions, costs are shared between drivers and passengers using the following formulation:

$$\boxed{V(Cost)_{CD} = \beta_{Cost} CarCost_{OD} \left[1 - \frac{S(O_{CD} - 1)}{O_{CD}}\right]} \qquad (4.9)$$

$$\boxed{V(Cost)_{CP} = \beta_{Cost} CarCost_{OD} \left(\frac{S}{O_{CP}}\right)} \qquad (4.10)$$

where:

β_{Cost} is the cost parameter, estimated across all modes in the model

$CarCost_{OD}$ is the car cost, including parking costs at the destination

S is the cost-sharing factor

O_{CD} is the mean occupancy for car driver observations in the HI (by purpose)

O_{CP} is the mean occupancy for car passenger observations in the HI (by purpose).

If S takes a value of 0, there is no cost sharing and the driver pays the full cost. If S takes a value of 1, there is equal sharing, that is, drivers and passengers pay an equal share.[7] Intermediate values of S imply both drivers and passengers contribute towards the total cost, but the driver pays a greater share.

We used mean occupancies in place of observed values because the occupancy is not known for PT and non-motorised mode observations. The mean occupancy values vary with purpose and are summarised in the following table.

Table 13: Mean Occupancy Values

Purpose	Car Driver	Car Passenger
Commuting	1.135	2.246
Home-Business	1.112	2.143
Home-Education	1.436	2.386
Home-Shopping	1.587	2.766
Home-Other Travel	1.356	2.546

We took the values of S from runs of the HI models, documented in Section 6.1. We used the HI because it contains more accurate information about passengers than the RSI, where it is necessary to make assumptions about the purpose and destination of passengers' trips.

Note that models that only represent drivers still apply the cost-sharing formula, on the basis that although the passengers are not modelled, the tests made on the HI data suggest the passengers would pay a share of the costs. This treatment also ensures that when the intercept and household datasets are pooled, costs are treated consistently throughout.

4.4.3 Car Availability Parameters

The car ownership and licence holding information required to define the car availability parameters was only available in the HI data. As a result, only models estimated from that dataset contain car availability parameters.

Substantial improvements in model fit can be achieved by specifying terms relating to levels of car availability in the models, which are determined as a function of:

- individual licence holding
- household licence holding
- household car ownership.

On the car driver alternative, 'car competition' terms are defined if there are more licence holders than cars in the household. In such cases, there is competition for the cars in the household and consequently the likelihood of a given individual having a car available is lower. We add constants

7 Strictly, this is only true if $O_{CD} = O_{CP}$, whereas in reality $O_{CP} > O_{CD}$. If observed occupancies were used, equal sharing would occur; the problem is that for non car-observations we do not know what the occupancy would have been and so have to use mean occupancies instead.

to the models to reflect the lower probability of choosing car driver when there is car competition.

For the car passenger alternative, the probability of travelling as a passenger is substantially higher if another household member is able to provide a lift. This is possible if at least one other household member has a licence, and there are one or more cars in the household. We use this condition to specify 'passenger opportunity' terms. These passenger opportunity terms may be interacted with household size; in larger households there may be 'competition' for the lifts and so the likelihood of travelling as a passenger is lower than in two-person households. It should be noted that car passenger is available if the number of cars in the household is zero, as individual's can obtain lifts from persons outside their household, but that the passenger opportunity term is not applied and therefore the predicted probability of car passenger being chosen is substantially lower.

Setting this out in notation form, define:

- $L_i(0,1)$ as individual licence holding
- $H = \Sigma_i L_i$ as household licence holding, summed over individuals
- C as household car ownership.

For the car driver, the alternative is only available if $L = 1$ and $C \geq 1$ (see Section 4.2.2). Then car competition is defined as $H > C$.

For the passenger, the passenger opportunity term is applied if $C \geq 1$ and $H – L > 0$.

4.4.4 Socio-Economic Parameters

The intercept surveys did not collect socio-economic data and therefore we added socio-economic parameters only to those models estimated from the HI data.

In addition to the licence holding and car ownership information, a substantial amount of socio-economic information is available from the HI surveys, which allows socio-economic terms to be added to improve the model fit. The following variables are available:

- age
- gender
- working status (full-time worker, full-time student, retired etc.)
- occupation.

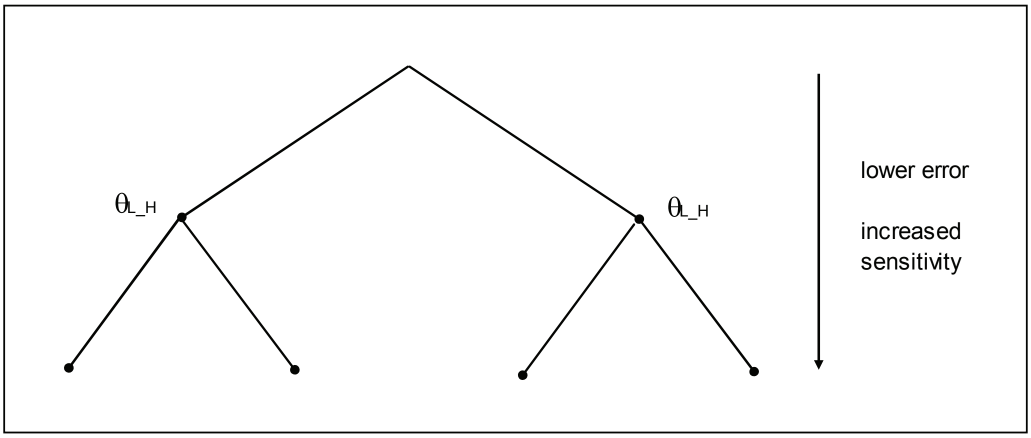
These variables have been used to test for socio-economic parameters, usually to improve mode choice. These parameters are identified by comparing the model predictions against observed data across a range of socio-economic segmentations. Model application is performed using the estimation software.

4.5 Structural Tests

As we noted earlier, we undertook the initial model development with multinomial models, i.e. destination, time period and (where included) mode choice, all equally sensitivity to changes in utility. A key objective of this study is to investigate the relative sensitivities of the different choice decisions, and therefore we made structural tests that provide direct estimates of the relative sensitivities of the different choice decisions.

To perform the structural tests, we set up nested logit structures with the different choices represented at different levels in the structure, as illustrated in Figure 4.

Figure 4: Nested Structures



Choices represented lower down in the structure have lower levels of error, and are more sensitive to changes in utility. The structural parameter θ_{L_H} defines the relative levels of error in the lower and higher levels of the structure, where L denotes lower level and H denotes higher level:

$$\boxed{\theta_{L\_H} = \frac{\sigma_L}{\sigma_H}} \tag{4.8}$$

where: σ_L is the standard deviation in the utilities at the lower level

σ_H is the standard deviation in the utilities at the higher level.

For the structure to be valid the condition $\sigma_H \geq \sigma_L$ should hold, which gives the condition $0 \leq \theta_{L\_H} \leq 1$. If a model is estimated that gives $\theta_{L\_H} > 1$ then the structure is rejected, and a structure would be tested with the higher and lower levels reversed.

In utility terms, we define the utilities V_L at the lower level in the same way as the multinomial models given in equations 4.1 and 4.3. To calculate the utilities at the upper level we calculate a 'logsum' over the lower level alternatives in the nest:

$$\boxed{V_H = \beta_H + \theta_{L\_H} \log \sum_K \exp(V_L)} \tag{4.9}$$

where: β_H is a constant for the higher level choice, e.g. a destination constant

θ_{L_U} is defined above

K are the alternatives in the lower level nest.

4.6 Longitudinal Tests

Given the objectives of the study – to investigate the results of a change in the network – it is important to determine whether there is any difference in the impact of cross-sectional and longitudinal differences in utility.

For illustration, consider a single-parameter logit model in which a sensitivity parameter λ is estimated. Variants of this parameter can be used to investigate possible changes in sensitivity. In practice, of course, the models will be very much more complicated, involving nesting of the various components of choice (destination, mode, time period); complications arising from the simultaneous use of the different data sources (home, roadside and public transport interviews); estimation of the various time and cost components of the utility function; and socio-economic variables.

For before data, we can use a simple equation, estimating λ^B,

$$\boxed{p^B{}_j = \frac{\exp(\lambda^B u^B{}_j)}{\sum_k \exp(\lambda^B u^B{}_k)}} \qquad (4.12B)$$

but for after data the equation can be extended to

$$\boxed{p^A{}_j = \frac{\exp(\lambda^A u^A{}_j + \lambda^L \Delta u_j)}{\sum_k \exp(\lambda^A u^A{}_k + \lambda^L \Delta u_k)}} \qquad (4.12A)$$

where p_j is the probability of choosing alternative j, with superscripts B and A indicating the before and after cases;

u gives the utility in each case of each alternative

Δu indicates the change in utility from before to after (i.e. $\Delta u_j = u^A{}_j - u^B{}_j$)

λ^B measures sensitivity in the before case

λ^A measures sensitivity in the after case

λ^L measures sensitivity to *changes* in utility.

The temporal stability of the cross-sectional effect (that is, whether $\lambda^A = \lambda^B$) can be tested, but any additional behavioural impact of a longitudinal change can also be tested (that is, whether $\lambda^L = 0$).

This formulation essentially breaks down the argument that differential utilities cannot be used with disaggregate data. Here we postulate that costs at time B could have an influence on behaviour at time A (although the proposal remains resolutely against allowing later costs to influence earlier behaviour). This approach offers improved clarity (for example, distinguishing longitudinal and cross-sectional effects), the advantages of disaggregation, a test on the stability of the cross-sectional parameter, and the ability to insist that influences must operate in the appropriate way through time.

On a practical level, in order to make this test the longitudinal parameter λ_L needs to be estimated simultaneously with the other parameters, which comprise the terms in Δv_k. To achieve this, we set up a scaling structure for the after alternatives with dummy alternatives associated with the utility differences attached beneath the after alternatives, with a scale parameter equal to λ^L. This structure allowed the simultaneous estimation of λ^L together with the parameters that enter the utilities.

We ran longitudinal tests for those models that use a combination of before and after data, specifically:

- pooled intercept models, reported in Chapter 5
- pooled intercept and household interview models, reported in Chapter 7.

CHAPTER 5 Intercept Model Results

Section 5.1 presents results from the commute roadside interview (RSI) and public transport interview (PTI) models that were used to inform the rest of the intercept modelling. This represents steps 1 and 2 of the model development plan presented in Figure 1.

Section 5.2 presents the results from the combined before and after models that have been estimated from the RSI data, and also presents models estimated from the PTI data. In Section 5.3 we describe the pooled intercept models, estimated from both RSI and PTI data.

5.1 Initial Model Tests

5.1.1 Specifying Return Level-of-Service

The first (commute) models converted one-way trip level-of-service (LOS) by doubling the LOS for the observed trip. We devised a test whereby the weighted average LOS in the unsampled direction was used instead of a simple doubling of the LOS in the sample direction. Given that the distribution of trips across time periods is known, the expectation was that weighted average LOS would better represent average travel times in the unsampled direction than simply assuming the unsampled leg took place in the same time period as the sampled leg. The tests we undertook for the RSI data did indeed demonstrate a significant improvement in model fit if a weighted average over all time periods was used for the unsampled direction. To define the weights for the averaging, we used the commute tours in the HI data to determine the outward-return time period proportions.

For the PT data, we found it best to take an average of the AM-, inter- and PM-peak periods only. When off-peak LOS was included the model, fit was noticeably worse, which we believe to be due to infrequent off-peak services biasing the mean LOS.

5.1.2 Inclusion of Passengers

We made model tests with the RSI data where car passenger was modelled as well as car driver. To model car passenger from the RSI data, it was necessary to assume that the passenger's destination zone was the same as the driver's. If the driver was making a serve passenger trip, the passenger's purpose was recorded; but if the driver was also travelling to an out-of-home destination, the passenger's purpose was not known and so we assumed the passenger had the same purpose as the driver. Consequently the level of error in the passenger data is expected to be significantly higher than that in the driver data, where the destination and purpose are always known.

For each model purpose, models were run with and without passengers and the impact on the model results was assessed. We then used these runs to determine whether passengers should be retained in subsequent models.

The tests, run separately for each model purpose. revealed higher levels of error in the car passenger data for all model purposes, and the overall results were substantially improved when passengers were dropped. Therefore the final models for all purposes use car driver observations only.

5.2 Combined Model Results

5.2.1 Roadside-Interview Models

We estimate the combined RSI models by combining before and after data. A significant percentage of the data was excluded from the models for the following reasons:

- dropping car passenger records, 10–40% of data depending on purpose (see discussion in Section 5.1.2)
- imputed records, where the records were re-coded into different time periods to boost sample sizes in certain time periods, around 10% of records
- screenline crossing probability less than 0.5, 10–15% of records.

The model exclusions, together with full model results, are detailed in Appendix E. In this section we present summary results, namely implied values-of-time and the results from the structural and longitudinal tests.

For all the home-based purposes, the implied values-of-time were significantly improved when passenger observations were dropped from the models. Therefore we retained only driver observations in the final models and did not undertake processing to infer the passenger records for non-home-based (NHB) purposes.

Table 14 presents implied values-of-time (VOTs) for each of the RSI models, with the 95% confidence intervals presented alongside. The combined intercept models use a linear cost formulation and so these VOTs are calculated from the ratio of the cost and time parameters presented in Appendix E. For comparison the 2002 WebTAG values are presented alongside.

Table 14: Combined RSI Models, Implied Values-of-Time (£/hr)

Purpose	VOT	WebTAG
HB Commute	4.56 ± 0.18	5.04
HB Business	10.07 ± 2.80	21.86
HB Education	11.07 ± 3.95	4.46
HB Shopping	n/a	4.46
HB Other Travel	87.19 ± 32.29	4.46
NHB Business	3.92 ± 1.02	21.86
NHB Other Travel	5.41 ± 0.59	4.46

The implied VOT for commuting is consistent with the WebTAG value.

The business value is substantially lower than the WebTAG value, although it is substantially higher than the value estimated for commuting. Note that the value quoted in WebTAG is based upon the employer's valuation of the time, and individual business travellers may place a lower valuation on their time than their employer.

The education value is significantly higher than the WebTAG value, and more than double the value for commute. The high VOT results from the small magnitude of the cost parameter, which is not particularly well estimated (t=3.4). A similar result is observed for other travel where the implied VOT is even higher – again, the explanation is that the cost parameter is not well estimated (t=2.8) and small in magnitude, resulting in a high implied VOT.

For shopping the cost parameter is positive and insignificant and therefore it is not possible to calculate the implied VOT. In the 'other travel' model, cost is significant but not highly so (t=2.8) and the parameter is small in magnitude, resulting in a high implied VOT.

For NHB, the business value is substantially lower than WebTAG, a difference also noted for the home-based business model. The NHB other travel model VOT is close to the value given in WebTAG.

The relative sensitivity of destination and time period choice was tested following the approach outlined in Section 4.5. The results for a model structure with destination below time periods are summarised in Table 15.

Table 15: Combined RSI Models, Structural Tests

Purpose	θ_{D_TP}
HB Commute	$\rightarrow 0$
HB Business	$\rightarrow 0$
HB Education	$\rightarrow 0$
HB Shopping	$\rightarrow 0$
HB Other Travel	0.141 (2.1)
NHB Business	0.214 (1.2)
NHB Other Travel	$\rightarrow 0$

For the majority of purposes the structural parameter tends to zero[8], indicating that varying the utilities by time periods does little to explain the observed time period choices in the RSI data. The exception is other travel, where a structural parameter was identified, although it is only just significant at the 5% level and the value indicates significantly higher error in time period choice relative to destination choice..

The conclusion from these structural tests is that it is not possible to model time period choice with the RSI data, and therefore in the pooled intercept models reported in Section 5.3, time period choice for the RSI was dropped from the modelling.

The final test was the longitudinal test specified in Section 4.6. The results are summarised in Table 16. Results shown in italics indicate that the model did not converge; in these instances the values reported are those at the point at which the model failed. The test was not run for shopping because of the positive cost parameter in that model.

[8] In the estimations, the structural parameters slowly tended towards zero. Most runs did not converge after a high number of iterations, but the structural parameters at the point at which the runs were stopped were close to zero.

Table 16: Combined RSI Models, Longitudinal Tests

Purpose	λ^L
HB Commute	*-0.223 (11.5)*
HB Business	*0.310 (6.2)*
HB Education	*-0.469 (9.3)*
HB Shopping	n/a
HB Other	-0.362 (17.2)
NHB Business	*-0.123 (2.2)*
NHB Other	*-0.402 (15.1)*

Although only one of the models has converged, the general pattern is for a negative lambda parameter to be estimated. This result suggests a time-lag effect, whereby travellers in the after case are influenced by LOS both before and after scheme completion. This is illustrated by examining equation 4.12, with λ^A normalised to a value of 1:

$$p^A_j = \frac{\exp(v^A_j + \lambda^L \Delta v_j)}{\sum_k \exp(v^A_k + \lambda^L \Delta v_k)} \tag{6.1}$$

Expressing the utility differences explicitly gives:

$$p^A_j = \frac{\exp\left[v^A_j + \lambda^L (v^A_j - v^B_j)\right]}{\sum_k \exp\left[v^A_k + \lambda^L (v^A_k - v^B_k)\right]} \tag{6.2}$$

Grouping before and after utilities:

$$p^A_j = \frac{\exp\left[(1+\lambda^L) v^A_j - \lambda^L v^B_j)\right]}{\sum_k \exp\left[(1+\lambda^L) v^A_k - \lambda^L v^B_k)\right]} \tag{6.3}$$

If $-1 \le \lambda^L \le 0$ then after choices are explained by a weighted average of before and after utilities, with a more negative λ^L implying greater weight for the before utilities. Values of λ^L between -0.5 and -0.1 have been identified, which implies a greater weight for the after utilities, as would be expected. This finding may be evidence for a lag effect, where travellers do not fully perceive the improvements in LOS between the before and after cases.

It should be emphasised, however, that these form interim results in the model development process, and the definitive test of longitudinal effects, are from the final pooled models.

5.2.2 Public Transport Interview Models

We estimate the PTI models by combining before and after PTI data. For every purpose except education, at least 80% of observations were retained in estimation. For education, 25% of the data was excluded because there were no attraction data – education employment – in the destination zone and consequently only 55% of the original observations were retained in the estimation.

Appendix E details in full the model exclusions, together with the final parameter values. In the remainder of this section we summarise the implied VOT, and the results from the structural and longitudinal tests.

Table 17 presents implied VOTs for each of the PTI models, together with 95% confidence intervals. The PTI models used a linear cost formulation. For comparison the 2002 WebTAG values are presented alongside.

Table 17: Combined PT Models, Implied Values-of-Time (£/hr)

Purpose	VOT	WebTAG
HB Commute	2.91 ± 0.12	5.04
HB Business	n/a	Bus: 16.72, Rail: 30.57
HB Education	15.06 ± 6.28	5.04
HB Shopping	5.15 ± 0.53	4.46
HB Other Travel	1.19 ± 0.11	4.46
NHB Business	n/a	Bus: 16.72, Rail: 30.57
NHB Other Travel	2.42 ± 0.68	4.46

The VOT for commuters is lower than the WebTAG value; however, the WebTAG value is for all modes and PT VOTs are often observed to be lower than the all-mode average.

The VOT for business travellers is not presented because the in-vehicle time parameter is positive and insignificant in the business model.

The high VOT for education travellers results from a weakly identified cost parameter, which is small in magnitude. Because the VOT is calculated as the ratio of the in-vehicle time and cost parameters, a small cost parameter results in a high VOT.

The VOT for shopping is consistent with the WebTAG values. The value for HB other travel is low, despite the high significance of the cost parameter in this model (t=18.0).

In the NHB business model the in-vehicle time parameter was positive and therefore the implied value-of-time is wrong-signed.

In the NHB other model the VOT is about half of the WebTAG value.

In Table 18, the access and egress time, wait time and transfers parameters are expressed relative to the in-vehicle time parameters, with t-ratios for the significance of the parameter ratios presented in brackets (relative to one for access & egress time and wait time because the issue is whether they are different in value to in-vehicle time, and relative to zero for transfers, where we are interested in the valuation). The transfer ratio reflects the equivalent number of minutes of in-vehicle time for each transfer. Results are not presented for business because the in-vehicle time parameter is positive and insignificant.

Table 18: Combined PT Models, Parameter Ratios

Purpose	Access & Egress Time	Wait Time	Transfers
HB Commute	0.76 (11.1)	1.33 (7.2)	0.8 (1.0)
HB Business	n/a	n/a	n/a
HB Education	0.75 (6.6)	1.19 (2.8)	18.0 (8.7)
HB Shopping	1.53 (10.5)	1.92 (10.7)	26.4 (17.0)
HB Other Travel	1.12 (1.6)	0.96 (0.2)	42.8 (9.6)
NHB Business	n/a	n/a	n/a
NHB Other Travel	1.76 (6.0)	1.63 (3.5)	40.4 (9.2)

Standard weightings in assignment packages for access and egress time and wait time are two, and therefore in general the access and egress time and wait time ratios are low, with values lower than in-vehicle time observed in some cases.

The value of transfers for commuters is not significant. For other purposes, however, the disutility of each transfer is high, relative to in-vehicle time.

The relative sensitivity of destination and time period choice was tested following the approach outlined in Section 4.5. The results for a model structure with destination below time periods are summarised in Table 19.

Table 19: Combined PT Models, Structural Tests

Purpose	θ_{D_TP}
HB Commute	0.474 (4.4)
HB Business	0.268 (1.1)
HB Education	0.283 (0.8)
HB Shopping	*1.085 (0.0)*
HB Other Travel	$\rightarrow 0$
NHB Business	2.510 (3.5)
NHB Other Travel	$\rightarrow 0$

For commute, business and education the results suggest time period choice has more error than destination choice, although overall the structural parameters are not strongly estimated.

For shopping, the model would not converge but the value of the structural parameter at failure was close to 1, implying similar levels of error in time period and destination choice. Given this result the reverse structure was tested, that is, time periods beneath destinations – but this would not converge either.

For HB other travel the structural parameter tended to zero implying there was no information on time period choice.

For NHB business the structural parameter is greater than 1, but it should be emphasised that in this model the in-vehicle time parameter is positive, and cost is insignificant. The reverse structure, time periods below destinations, was also tested but the structural parameter was also significantly greater than 1. Therefore there is no clear evidence for either structure.

For NHB other travel the structural parameter tended to zero implying there was no information on time period choice.

Overall there seems to be more information on time-period choice in the PT intercept data than in the RSI data, but the structural parameters are not well estimated and so this information is not strong.

The final set of tests we made was the longitudinal test specified in Section 4.6. The results are summarised in Table 20. Results shown in italics indicate that the model did not converge; in these instances the values reported are those at the point at which the model failed.

Table 20: Combined PT Models, Longitudinal Tests

Purpose	λ^L
HB Commute	*-1.095 (13.2)*
HB Business	n/a
HB Education	0.221 (0.9)
HB Shopping	-0.538 (4.0)
HB Other	-0.135 (1.1)
NHB Business	n/a
NHB Other	*-0.115*

The test was not run for HB business because the PT in-vehicle time parameter has the wrong sign. Of the three runs that have converged, only shopping has yielded a significant longitudinal parameter and so overall there is little evidence of a longitudinal effect from the combined PT models.

5.3 Pooled Intercept Model Results

We re-estimated the pooled intercept models by pooling the RSI and PTI data (before and after).

For commute, the RSI data indicated no information on time period choice, and tests from the PTI data indicated the same. Therefore time period choice was not incorporated in the pooled intercept models. We tested mode choice between car driver and PT but structural tests of the relative sensitivity of mode and destination choice indicated that the pooled intercept data provided little information on mode choice. Therefore mode choice was also dropped from the structure, which then collapsed to destination choice only.

Based on the findings of the combined RSI and PTI models, we did not model time period choice for business. The initial structure included mode choice, but, like commuting, the structural parameter tended to zero, indicating that the pooled intercept data provided little information on mode choice. Consequently the final pooled intercept model for business travel reflected destination choice only.

The same finding was obtained for education travel, where time-period choice was not represented, and the structural tests demonstrated that the pooled data provided little information on mode choice. The final model is once again destination choice only.

For shopping and other travel, time-period choice was included in the model structure based on the structural tests undertaken for the separate RSI and PTI models. However, once again the structural tests indicated that the pooled dataset provided little information on mode choice. Furthermore, the pooled results for other travel indicated there was little information on time-period choice in the pooled intercept data. Therefore only shopping retains time-period choice in the final model structure.

In summary, with the exception of shopping all the pooled intercept models represent destination choice only.

> The pooled RSI and PTI data are unable to support the modelling of either mode or time period choice.

The implied VOT in the final models are summarised in Table 21, with 95% confidence intervals presented alongside. For each purpose, the cost parameter is estimated jointly across datasets.

Table 21: Pooled Intercept Models, Implied Values-of-Time, £/hr

Purpose	Car VOT	PT VOT	WebTAG
HB Commute	4.35 ± 0.16	2.93 ± 0.14	5.04
HB Business	5.23 ± 1.09	1.58 ± 0.72	Car: 21.86 Bus: 16.72 Rail: 30.57
HB Education	33.42 ± 9.8	8.87 ± 2.40	4.46
HB Shopping	26.12 ± 1.91	3.45 ± 0.35	4.46
HB Other Travel	22.89 ± 1.75	1.85 ± 0.22	4.46
NHB Business	5.10 ± 0.57	3.70 ± 1.48	Car: 21.86 Bus: 16.72 Rail: 30.57
NHB Other Travel	23.10 ± 1.54	9.25 ± 1.68	4.46

The commute VOTs are consistent with those in the separate RSI and PTI intercept models, because the separate RSI and PTI models had cost parameters with similar magnitudes. For car, the VOT are in line with the WebTAG (all mode) value. The value for PT is lower but this is a common result in such models.

For business, the implied VOTs are substantially lower than that given in WebTAG, but close to the commute value. The value for PT is also in line with the commute estimate. (It was not possible to estimate a VOT from the PT-intercept data only because the PT in-vehicle time parameter had the wrong sign.)

For education the car VOTs are extremely high, and the PT value is also high relative to the WebTAG values. The car value has risen relative to the RSI model because merging with the PT data results in a smaller cost parameter, and in turn a higher implied VOT.

The car VOT are consistently higher than the PT values, sometimes substantially so. We do not believe this to be a mode-type effect, that is, that car is viewed as less comfortable than PT. Rather this is likely to be a user-type effect, namely that PT users have lower incomes on average, and there may be differences in mean trip length between modes that cause differences in VOTs, for example car trips for shopping. Other travel intercepted in the RSI may be infrequent long-distance trips with high VOTs.

The extremely high shopping VOT for car are related to the problems in estimating cost in the shopping RSI model (reported in Section 5.2.1). Because of the problems with the cost parameter, the car time parameter is large in this model (car time proxies for both car time and cost) and when this is combined with a small cost parameter in the pooled model, it results in extremely high VOT.

The NHB business VOT are much lower than those given in WebTAG, and in line with the values for commuting. A possible explanation for this is that WebTAG gives employer's valuations, whereas individuals may be making decisions based upon their (lower) personal valuations of time.

The NHB other VOT are high for both car and PT as a result of a small cost parameter in the pooled model.

Only one structural test was possible with the pooled models – a test of the relative sensitivity of time period and destination choice for shopping. We tested a structure with destinations beneath time periods and the structural parameter was 0.209 (t=3.2), implying substantially higher error in time-period choice relative to destination choice.

The results from the longitudinal tests are summarised Table 22. We ran these for the final model specifications, that is, models of destination choice only except for shopping, where time-period choice was also modelled. Results shown in italics indicate that the model did not converge; in these instances the values reported are those at the point at which the model failed.

Table 22: Pooled Intercept Models, Longitudinal Tests

Purpose	λ^L
HB Commute	*-0.180 (9.7)*
HB Business	-0.295 (4.0)
HB Education	*0.774 (13.6)*
HB Shopping	*-0.433 (17.6)*
HB Other	
NHB Business	-0.340 (5.8)
NHB Other	*-0.444 (19.3)*

CHAPTER 6 Household Interview Model Results

As we discussed in Chapter 5, the household interview (HI) models were first developed as stand-alone models. Non-home-based models were not developed from the HI data.

In Section 6.1 we describe the cost specifications used in the models, and discuss the optimum formulation for entering cost into the utilities, and the results of tests to investigate how to allocate car costs between drivers and passengers. Section 6.2 documents the final level-of-service specification in the models, and presents validation of the out-of-vehicle components for public transport. The car availability and socio-economic parameters identified are documented in Sections 6.3 and 6.4 respectively. Finally, in Section 6.5 we present the results of the structural tests to investigate the relative sensitivity of destination, mode and time-period choices.

Once a near final specification had been determined, we pooled the HI models with the intercept models documented in the previous chapter to determine the final models for each purpose. These models are documented in Chapter 7.

Appendix F documents the volume of data that that was excluded prior to model estimation, which was less than 10% for each journey purpose. It also presents full parameter results for the final model specifications.

6.1 Cost Specifications

For most model purposes, the best model fit was obtained with cost entering the utilities in separately linear and log-cost terms. The log-cost term has the most effect at the short-distance trip range. For employer's business, where trip lengths are longer and the volume of data is lower, it was not possible to identify both linear and log-cost terms; the final model contains a log-cost term only.

As we discussed in Section 4.4.2, costs are allocated between drivers and passengers using a cost-sharing formulation. We determined the optimum value of the sharing factor S in these formulae by testing different values of S, measuring the impact on the model fit, which varied according to the journey purpose. We made these tests after the tests of linear and log-cost, as these were found to impact upon the optimum value for S. The results are summarised in Table 23, together with the mean observed occupancies.

Table 23: Car Cost Sharing Parameters S

Purpose	S	Mean Driver Occupancy	Mean Passenger Occupancy
Commuting	0.25	1.135	2.246
Employer's Business (EB)	0.0	1.112	2.143
Education	0.4	1.436	2.386
Shopping	0.3	1.587	2.766
Other Travel	1.0	1.356	2.546

For employer's business the sharing parameter is zero, which may reflect the fact that it's the business, not the driver, that pays and in that sense occupancy does not influence the cost. For commuting, education and shopping similar values are obtained, which implies that cost-sharing takes place but that the driver pays a larger share of the costs. For other travel the pattern is different, with full cost-sharing, i.e. drivers and passengers pay equal shares of the total cost.

No clear pattern between the optimum value of S and the mean occupancy is apparent.

We also used these values in the final intercept models, documented in Chapter 5, and in the pooled intercept and HI models documented in Chapter 7.

6.2 Level-of-Service Terms

The basic level-of-service (LOS) specification was set out in Section 4.4.1. However for all purposes except shopping it was not possible to identify a significant parameter for the number of transfers. To assess the reasonableness of the out-of-vehicle parameters, Table 24 expresses out-of-vehicle components relative to in-vehicle time. The r-ratios in brackets define the significance of the ratio relative to a value of one.

Table 24: HI PT Out-of-Vehicle Parameter Validation

Purpose	Access & Egress Time	Wait Time	Transfers
HB Commute	0.76 (2.0)	0.90 (0.5)	term not significant
HB Business	0.23 (3.0)	0.52 (0.5)	term not significant
HB Education	0.62 (4.9)	0.49 (5.0)	term not significant
HB Shopping	1.20 (1.2)	1.47 (1.8)	term not significant
HB Other Travel	0.87 (1.2)	1.14 (0.9)	term not significant

Compared to expected weighting around two the relative valuations of access and egress time and wait time are low, in most cases weighted less than in-vehicle time.

The low values of out-of-vehicle components relative to in-vehicle time, and the inability to identify significant transfers terms, suggests that the PT LOS does not provide a good measure of the actual out-of-vehicle components faced by travellers in the household interview.

6.3 Car Availability Variables

The addition of car availability parameters produced significant improvements in model fit as a result of an improved explanation of mode choice. (The specification of car availability parameters is discussed further in Section 4.4.3.)

The terms identified in the models are summarised in Table 25. The base level for the car driver terms is car freely available, i.e. the number of household licences is greater or equal to the number of household cars. The base level for the car passenger terms is that no passenger opportunity exists in the household.

Table 25: Car Availability Parameters

<table>
<tr><th></th><th></th><th>Commute</th><th>Business</th><th>Education</th><th>Shopping</th><th>Other Travel</th></tr>
<tr><td rowspan="2">Car Driver</td><td>Car competition, 1 car in hh</td><td>✓</td><td>✓</td><td rowspan="2">✓</td><td>✓</td><td rowspan="2">✓</td></tr>
<tr><td>Car competition, 2+ cars in hh</td><td>✓</td><td></td><td>✓</td></tr>
<tr><td rowspan="2">Car Passenger</td><td>Pass. opportunity, 2 persons in hh</td><td>✓</td><td></td><td>✓</td><td>✓</td><td>✓</td></tr>
<tr><td>Pass. opportunity, 3+ persons in hh</td><td>✓</td><td></td><td>✓</td><td>✓</td><td>✓</td></tr>
</table>

The volume of car passenger data for business is low (23 observations) and this makes identifying significant passenger opportunity terms difficult. Furthermore, travelling as a passenger with another household member is unlikely when travelling on business.

6.4 Socio-Economic Parameters

The socio-economic parameters we identified vary considerably according to the tour purpose and are summarised in Tables 26–30. The sign of the term determines whether it increases (positive) or decreases (negative) the probability of choosing that mode. The model parameters are estimated relative to the segments of the classification in question for which terms are not defined; taking a simple example, the male terms are defined relative to females. The classifications are defined in full in Appendix C.

Table 26: Commute Socio-Economic Parameters

Term	Mode	Sign	Definition
SEGAB_PT	PT	+	Individuals in socio-economic groups A&B (professional and managerial) are more likely to choose PT
SEGC1_PT	PT	+	Individuals in socio-economic groups C1 (skilled non-manual) are more likely to choose PT
MaleCycle	Cycle	+	Males are more likely to cycle
SEGDE_Walk	Walk	+	Individuals in socio-economic groups DE (partly skilled, unskilled) are more likely to walk
PTwkWalk	Walk	+	Part-time workers are more likely to walk

Table 27: Business Socio-Economic Parameters

Term	Mode	Sign	Definition
FTwk38Walk	Walk	-	Full-time workers who work 38+ hours per week are less likely to walk

Table 28: Education Socio-Economic Parameters

Term	Mode	Sign	Definition
MaleCarD	CarD	+	Males are more likely to drive
CarP_0_10	CarP	+	Individuals aged 0–10 are more likely to travel as a car passenger
CarP_11_15	CarP	+	Individuals aged 11–15 are more likely to travel as a car passenger
PT_0_10	PT	-	Individuals aged 0–10 are less likely to travel by PT
FTstuPT	PT	+	Full-time students are more likely to travel by PT
Walk_16_20	Walk	-	Individuals aged 16–20 are less likely to walk

Table 29: Shopping Socio-Economic Parameters

Term	Mode	Sign	Definition
CarP_0_10	CarP	+	Individuals aged 0–10 are more likely to travel as a car passenger
RetiredCrP	RetiredCrP	+	Retired Persons are more likely to travel as a car passenger
PTstudent	PT	+	Full-time students are more likely to travel by PT
WalkStudnt	Walk	+	Full-time students are more likely to walk

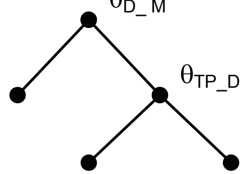
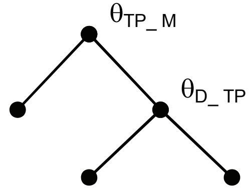
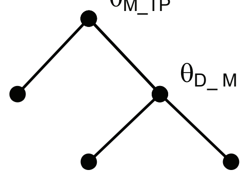
Table 30: Other Travel Socio-Economic Parameters

Term	Mode	Sign	Definition
0to10CarP	CarP	+	Individuals aged 0–10 are more likely to travel as a car passenger
RetiredCrP	CarP	+	Retired persons are more likely to travel as a car passenger
MaleCarP	CarP	-	Males are less likely to travel as a car passenger
0CarPT	PT	+	Individuals in zero car households are more likely to travel by PT
RetiredPT	PT	+	Retired persons are more likely to travel by PT

6.5 Structural Tests

We performed structural tests on the final multinomial model specification, and investigated the relative sensitivities of destination, mode and time period choice by estimating models for each of the six possible structural combinations for these three choices. As discussed in Section 4.5, choices placed lower down in the structure have lower levels of error and higher levels of sensitivity to changes in utility. There are six possible structures for destination, mode and time period choice. However, our early tests revealed that mode choice was consistently above destination choice, that is, that there is more error in mode than destination choice. Therefore the results we present here are for the three structures where mode choice is above destination choice. Table 31 summarises the results. The values reported are the structural parameters (as defined in Section 4.5) with two sets of t-ratios given in brackets. The first gives the significance of the structural parameter relative to zero, the second the significance relative to 1. Results in italics show model structures that did not converge; in such cases the results at the point of failure are reported.

Table 31: Household Interview Structural Tests

			Commute	Business	Education	Shopping	Other
Str A	Modes	 θ_{D_M}	0.518 (4.6, 4.3)	*0.072 (0.3, 3.9)*	0.468 (6.2, 7.0)	0.224 (3.1, 10.7)	0.180 (2.7, 12.3)
	Dests	θ_{TP_D}	6.59 (2.8, 2.4)	*44.6 (0.3, 0.3)*	2.19 (3.2, 1.7)	2.71 (2.1, 1.3)	5.38 (3.2, 2.6)
	TPs						
Str B	Modes	 θ_{TP_M}	*179 (0.4, 0.4)*	*1.96 (0.3, 0.1)*	0.386 (4.0, 6.4)	0.339 (2.1, 4.1)	0.368 (2.5, 4.3)
	TPs	θ_{D_TP}	*0.003 (0.4, 133)*	*0.416 (0.4, 0.6)*	1.23 (5.1, 1.0)	0.774 (2.6, 0.8)	0.469 (1.8, 2.0)
	Dests						
Str C	TPs	 θ_{M_TP}	-0.774 (1.1, 2.5)	*0.012 (0.4, 33)*	4.43 (4.2, 3.3)	1.18 (1.7, 0.3)	10.2 (1.7, 1.5)
	Modes	θ_{D_M}	0.485 (4.4, 4.7)	*0.287 (1.1, 2.7)*	0.485 (6.6, 7.0)	0.280 (4.1, 10.5)	0.121 (1.9, 13.8)
	Dests						

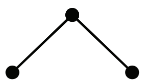
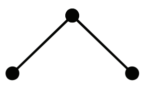
For commute and employer's business, the results demonstrate that accessibility, measured by a logsum over modes and destinations, provides little information to model time period choice. This is demonstrated most clearly by Structure C, with time period choice at the top. In both cases the logsum over modes and destinations has an insignificant structural parameter, and for commute the term is negative.

For education, it was clear from the results for Structure A and Structure C that destinations should be below modes; but the results for time period choice were unclear, as none of the three structures yielded acceptable results for both structural parameters. The results from Structures A and B suggest time period choice should move up the structure; but in Structure C, with time periods at the top, the results are not acceptable, as the structural parameter for mode and time period choice is significantly greater than 1.

Therefore for commute, business and education time period choice was dropped from the modelling. It should be noted that the models represent large time periods only, and for commute, business and education, where activity times are typically fixed, this means there is little scope for switching between time periods in response to congestion, unless the individual's journey time happens to occur around the boundary between two time periods.

Having dropped time period choice, we made model runs for the two possible mode and destination structures.[9] The results are summarised in Table 32, with the t-ratios with respect to zero and 1 respectively given in brackets.

Table 32: Commute, Business and Education HI Structural Tests

			Commute	Business	Education
T1	Dests Modes		1.63 (13.3, 5.1)	6.09 (5.5, 4.6)	
T2	Modes Dests		0.424 (4.3, 5.8)	0.299 (1.4, 4.7)	0.482 (6.5, 7.0)

In the commute model the T2 structure with destinations below modes is the best; this is consistent with the tests reported in Table 31. For business the same result is obtained but the structural parameter is not significantly different from zero, although it is significantly different from one. We should emphasise that there are only 288 observations in the business model. Finally the education model also indicates mode choice to be beneath destinations.

For mandatory purposes, the HI results show destination choice to be more elastic than mode choice. The results also suggest the HI data provide little information about time period choice.

For both shopping and other travel, the best structure seems to be modes above time periods above destinations. However, the structural parameters are not significant in these runs – with one exception.

9 For education, only the T2 structure was run based on the findings of earlier tests.

For maintenance/discretionary purposes, the HI results again show destination choice to be more elastic than mode choice. The results also show that time period choice is more elastic than mode choice but less elastic than destination choice; however, the evidence for this finding is not strong.

As the HI models are estimated from after data only, the longitudinal test described in Section 4.6 has not been made.

CHAPTER 7 Pooled Model Results

In this chapter we discuss the results of the pooled intercept and household interview (HI) models, which represent the final stage in the model development. Here, rather than refer repeatedly to the intercept and HI datasets, we term these ‘pooled models’.

7.1 Model Structure

We decided which responses to represent in the pooled models in the light of the outcome of the structural tests made for the pooled intercept models (reported in Section 5.3) and the HI models (reported in Section 6.5).

The conclusion from the pooled intercept models was that the data did not support the modelling of either mode or time period choice, and therefore in the pooled models we used the intercept data to model destination choice only. This means that all information on the relative sensitivity of different choices is made on the basis of the household interview data alone.

Therefore the role of the intercept data in the final models is to improve the estimates of the cost, in-vehicle and out-vehicle time parameters.

Following the structural tests made for the HI models, for commute, business and education the HI data are used to model mode and destination choice; for shopping and other travel the HI data are used to model mode, destination and time period choice.

The structural tests that we ran were based on the outcomes of the HI structural tests. This meant the following structures were tested for comparison against a multinomial model:

- commute – modes above destinations
- business – modes above destinations
- education – modes above destinations
- shopping – modes above time periods above destinations
- other travel – modes above time periods above destinations.

7.2 Model Specification

We estimated the socio-economic parameters in the models from the HI data alone. Therefore the car availability and socio-economic parameters were estimated using the same specifications as those in the HI-only models, reported in Sections 6.3 and 6.4.

It should be emphasised that the cost parameters, as well as other LOS parameters for in-vehicle and out-vehicle components, are estimated jointly across the intercept and HI datasets. As the intercept dataset is substantial, the intercept data have a corresponding impact on the cost and LOS parameters in the final models.

The cost formulations used were initially based on the results from the HI tests, described in Section 6.1. However when the pooled models were estimated, we had to revise some of the cost specifications.

For business, the log-cost only formulation resulted in a positive car time parameter; when a linear-cost only formulation was tested instead, the car time parameter improved but PT in-vehicle time became insignificant. The final model specification used linear-cost only, and a separate PT in-vehicle time parameter for the PT intercept data, which was identified as the cause of the difficulties with the cost and time parameters. In the PT intercept model for business, reported in 5.2 a positive PT in-vehicle time parameter was also obtained.

For other travel, the linear cost parameter was positive in the pooled model and was therefore dropped. The results with log-cost alone were plausible.

A final consideration was the impact of the weights on the HI records. The HI-only models were run without weights, which is theoretically valid because the screenlines have no impact upon the likelihood of tours being sampled. However, in the pooled models the HI records receive weights according to the probability that the household was sampled and that the trip crossed a screenline. This is necessary because in the HI short-distance trips have a higher weight to compensate for the fact that they cannot be interviewed in the intercept surveys. During the development of the pooled commute model, we discovered that a few high-weight observations were significantly biasing the model results. Therefore households with a weight of greater than 1,000 were excluded from the estimations, which resulted in a maximum of nine tours being excluded for any given purpose.

7.3 Model Results

It is useful to review the estimates for the dataset scaling parameters in each model, together with the estimation samples, to assess the relative contribution each dataset makes to the final model. As we explained in Section 4.3.4, the scales express the levels of error in each dataset relative to the HI data. These data are summarised in Table 33.

Table 33: Dataset Sample Sizes and Scaling

	HI	RSI before		RSI after		PT before		PT after	
	Obs	Obs	Scale	Obs	Scale	Obs	Scale	Obs	Scale
Commute	3,719	19,904	0.746	26,449	0.747	12,803	0.920	12,203	0.700
Business	287	2,474	0.914	2,715	1.041	594	1.097	1,177	0.979
Education	4,067	398	0.472	869	0.453	2,080	0.843	1,685	0.572
Shopping	2,440	4,183	0.896	6,953	0.611	4,092	0.691	2,630	0.520
Other	4,807	10,655	0.729	13,261	0.626	4,172	0.445	4,894	0.368

Comparing the number of observations by dataset, it can be seen that the intercept surveys typically provide substantially larger samples than the household interview. The exception is education where, due to the importance of car passenger and non-motorised modes, the HI sample is the largest.

The majority of the scale parameters lie in the range 0.5–1, implying that the intercept datasets have higher levels of error than the HI data. This is plausible because the HI data are tour data whereas the intercept data only have information from one journey direction; the LOS used to model the HI data is for the correct combination of outward and return time period, while average LOS is used for the intercept data, for the leg in the unsampled direction. A further factor is that the HI models include socio-economic parameters that improve the fit of the model to the observed choices and therefore reduce levels of error in modelling the HI data.

With the exception of education, the combination of sample size and error scale means that the intercept surveys contribute most to the jointly estimated cost and level-of-service parameters.

To check the PT out-of-vehicle LOS components, we calculated the ratios of the parameters to the PT in-vehicle time parameters. These are presented in Table 34, with the t-ratios of the parameter ratios (relative to a value of one for access & egress time and wait time, because the issue is whether they are different in value to in-vehicle time, and zero for transfers) presented in brackets.

Table 34: HI PT Out-of-Vehicle Parameter Validation

Purpose	Access & Egress Time	Wait Time	Transfers
HB Commute	0.55 (17.6)	0.36 (20.9)	8.20 (10.6)
HB Business	0.15 (14.7)	0.78 (1.0)	73.2 (4.7)
HB Education	0.53 (10.4)	0.52 (7.3)	term not significant
HB Shopping	0.88 (2.6)	1.08 (0.4)	119.2 (10.5)
HB Other Travel	0.99 (0.2)	0.79 (4.0)	23.3 (14.9)

Despite the fact that the parameter values are generally well estimated, the relative valuations of access and egress time and wait time remain low, with values less than 1 in the majority of cases. As we discussed in Section 6.4, these low valuations suggest that the LOS for out-of-vehicle components does not accurately reflect the actual travel times faced by individuals.

The relative impact of the cost and time terms are validated through the examination of the implied VOT and presented in Chapter 8.

7.4 Structural Tests

For all model purposes the model structure was determined on the basis of information from the HI alone. Rather than run tests for all possible structures, we ran the best structure identified from the HI model.

Tables 35 and 36 summarise the results for mandatory purposes, where only mode and destination choices are represented, and maintenance/discretionary purposes, where time period choice is represented as well as mode and destination. In both cases the results from the HI-only models from Chapter 6 are presented underneath. The significance of the structural parameters is indicated by the two t-ratios given in brackets; the first is expressed relative to zero and the second is expressed relative to one.

Table 35: Pooled Model Structural Tests, Mandatory Purposes

			Commute	Business	Education
Pooled	Modes Dests	θ_{D_M}	0.636 (21.3, 12.2)	0.225 (3.2, 11.0)	0.511 (10.7, 10.2)
HI only	Modes Dests	θ_{D_M}	0.424 (4.3, 5.8)	0.299 (1.4, 4.7)	0.482 (6.5, 7.0)

Table 36: Pooled Model Structural Tests, Maintenance/Discretionary Purposes

			Shopping	Other
Pooled	Modes	θ_{TP_M}	0.314 (5.3, 11.6)	0.059 (1.0, 17.9)
	TPs	θ_{D_TP}	0.797 (6.9, 1.8)	0.751 (6.4, 2.1)
	Dests			
HI only	Modes	θ_{TP_M}	0.339 (2.1, 4.1)	0.368 (2.5, 4.3)
	TPs	θ_{D_TP}	0.774 (2.6, 0.8)	0.469 (1.8, 2.0)
	Dests			

In general the results are consistent with the HI-only models, which is to be expected, as the structural parameters are estimated using information from the HI alone.

For commute, the structural parameter is larger in the pooled model, that is, the difference in the relative levels of error for mode and destination choice is less. It may be that the addition of the intercept data improves the modelling of mode choice through improving the cost and LOS parameters.

In the case of other travel, one of the structural parameters is not significantly different from zero in the pooled runs, and therefore the multinomial structure was retained. Note also that the structural parameters were not highly significant in the HI-only model so it seems that the evidence on structure in the household interview is not strong.

7.5 Longitudinal Tests

The longitudinal tests were run using the procedure set out in Section 4.6. The impact of cost changes in the after HI and intercept data was tested. We assumed that the longitudinal parameter λ_L did not vary between the HI and after intercept data.

The results from the tests are summarised in Table 37 and reported in full in Appendix G. Results in italics indicate that the model did not converge; the results at the point the run failed are reported. The models for shopping and other travel would not iterate at all and so no results are presented – the additional complexity introduced by modelling time period choice as well as mode and destination choices may contribute to the estimation problems.

Table 37: Pooled Model Longitudinal Tests

Purpose	λ^L
Commute	*-0.0211*
Business	*-0.637*
Education	*-0.583*

The results obtained provide some evidence that after behaviour can be explained as a weighted average of before and after LOS (see Section 5.2.1), although it should be noted that none of these models have converged.

CHAPTER 8 Pooled Model Validation

Validation statistics were generated for the final multinomial models and the structural tests documented in Chapter 7. The exception is other travel, where the nested structure was rejected and therefore only the multinomial model was validated.

8.1 Values-of-Time

Most models included a log-cost term, and as a result the implied values-of-time (VOTs) vary according to the journey cost (see Equation 4.8). Therefore the VOTs are best presented in graphical form to illustrate how they vary with cost. Figures 5–13 present VOTs for car and PT by purpose. VOTs are presented for multinomial (MNL) and nested models. With the exception of business, the VOTs vary according to cost, therefore the observed distributions of costs for the chosen car driver and PT observations have also been plotted to put the VOT distributions into context.

Figure 5: Pooled Commute Model VOTs

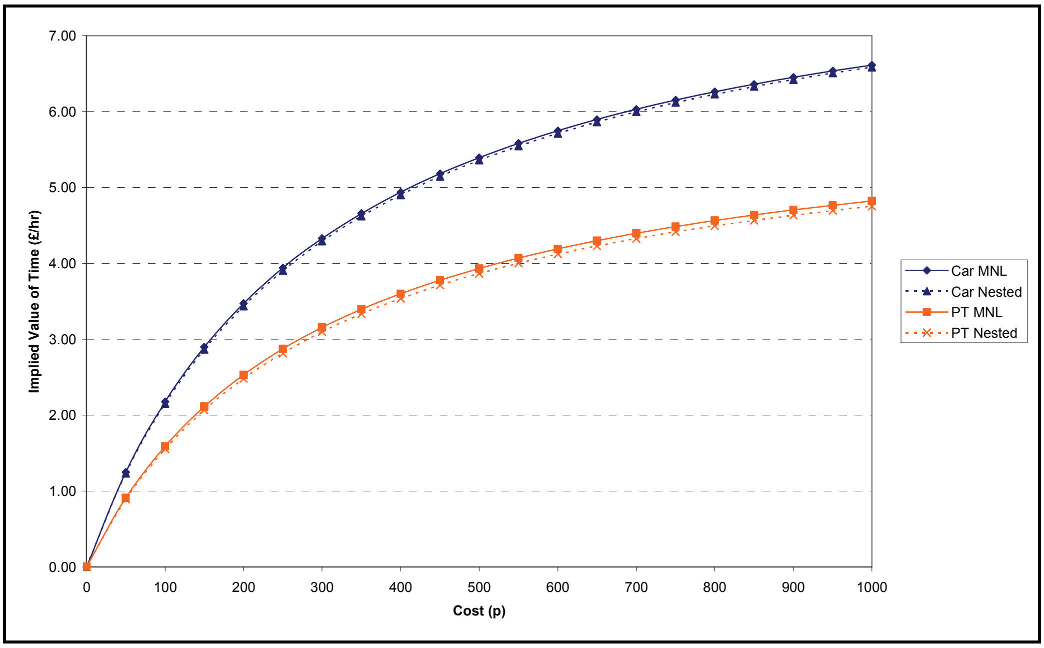
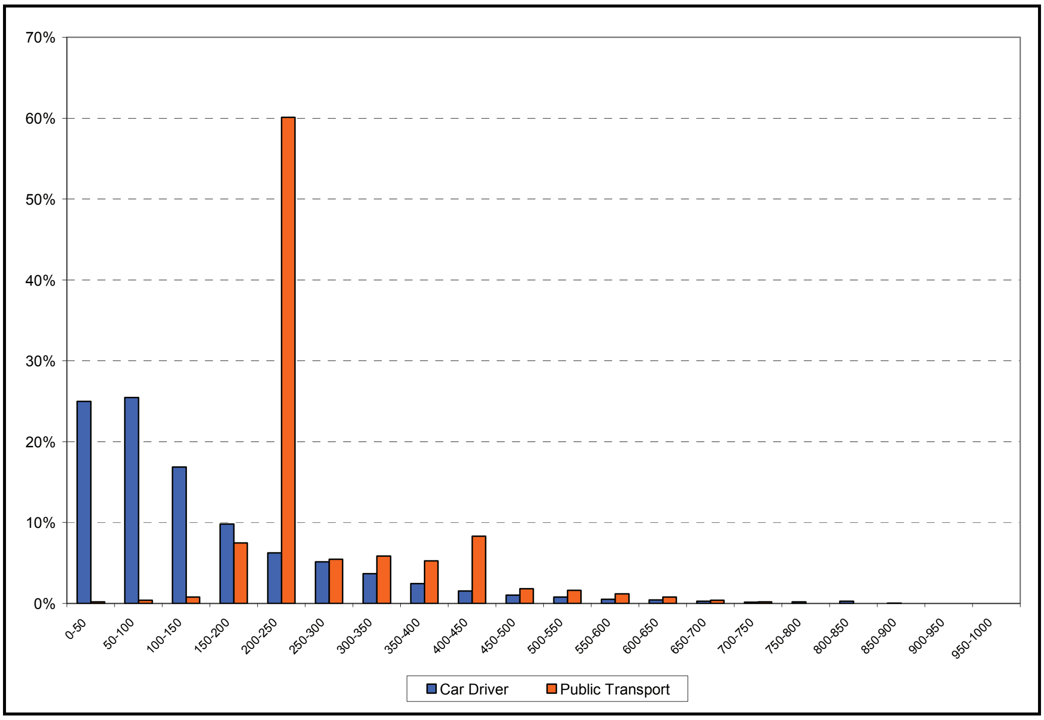
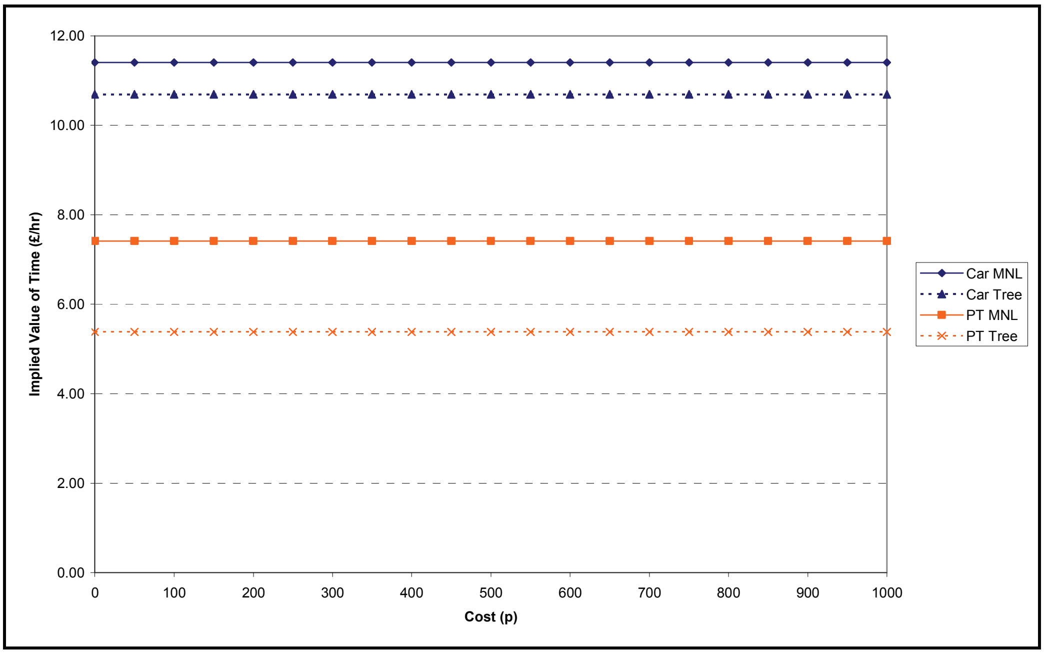


Figure 6: Pooled Commute Model Cost Distributions



For car driver the VOT range from zero to £3.40 per hour for costs up to 200p, which covers over three-quarters of the data. This is considerably lower than the WebTAG average VOT (£5.04 per hour), which equates to a journey of 400p in Figure 5. The observed cost distribution for public transport is much spikier, peaking at the 200–250p band, which gives implied VOT of £2.50–2.80 per hour. Again this falls below the WebTAG average value.

Figure 7: Pooled Business Model VOTs



Note that the business model is linear-cost only, consequently the VOT do not vary with journey cost. The VOTs are substantially higher than those for commute, but not as high as the employer's valuations given in WebTAG of £21.86 per hour for car, £16.72 per hour for bus and £30.57 per hour for rail. It is worth noting that the VOTs implied by the models are based on traveller time/cost trade-offs, rather than an employer cost formula.

The MNL VOT are higher than the tree values, particularly for PT.

Figure 8: Pooled Education Model VOTs

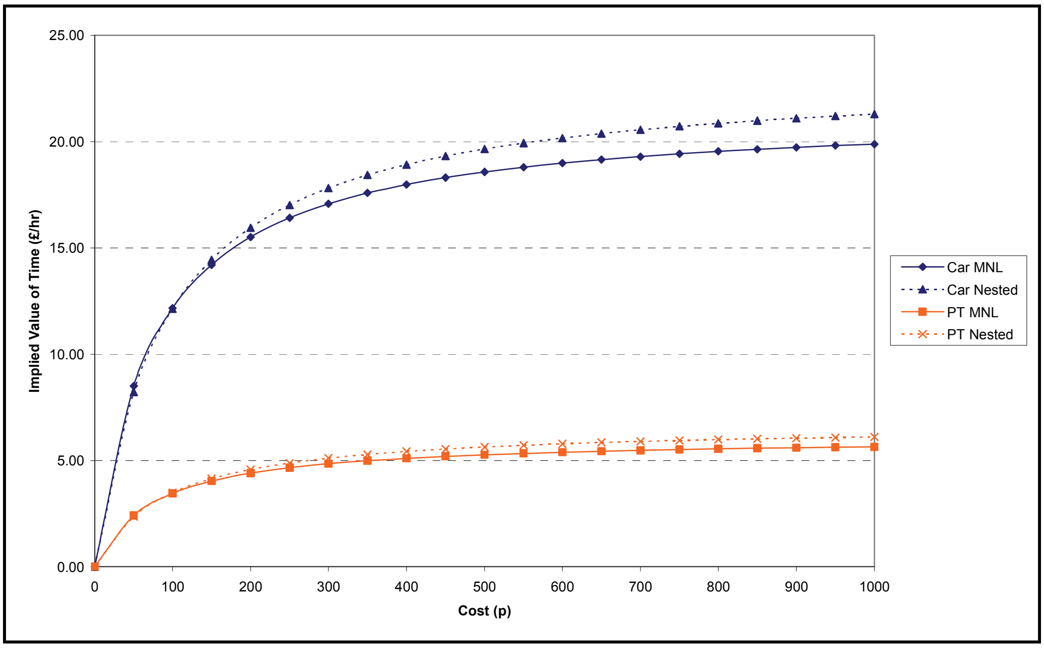
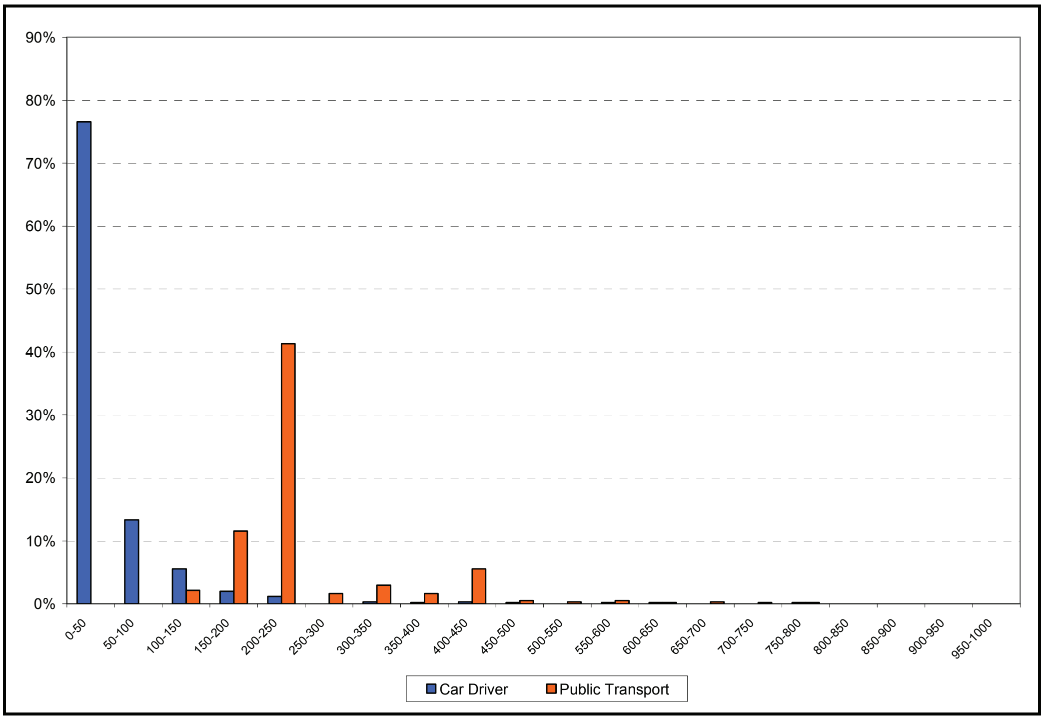


Figure 9: Pooled Education Model Cost Distributions



For car, the low mean costs mean that the VOT for typical journeys lie within the WebTAG range. Over three-quarters of journeys lie in the 0–50p range which gives VOT ranging from zero to £8.20 per hour compared to the WebTAG average value of £4.46 per hour. For PT, costs peak in the 250-300p band, which gives VOT of £4.80–5.10 per hour, consistent with the WebTAG value of £4.46 per hour.

Figure 10: Pooled Shopping Model VOTs

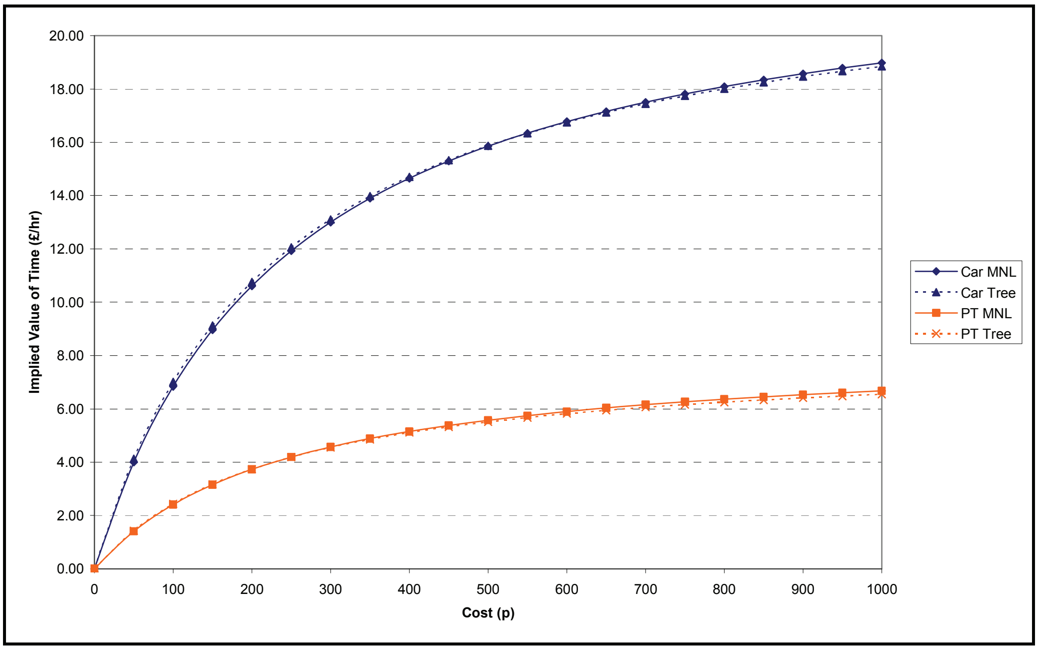
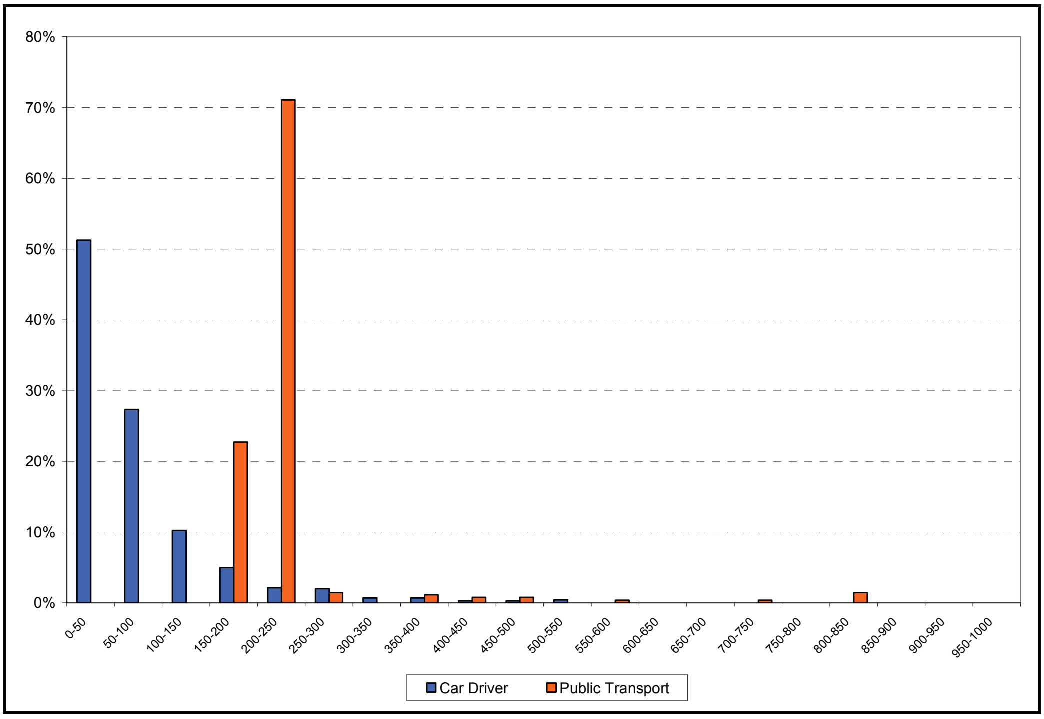


Figure 11: Pooled Shopping Model Cost Distributions



Over three-quarters of the observed car costs lie in the range 0–100p, which gives implied VOT ranging from zero to £7 per hour. For PT, costs peak at 200–250p, giving VOT of £4.20–4.50 per hour. In both cases this matches well with the WebTAG average of £4.46 per hour.

Figure 12: Pooled Other Travel Model VOTs

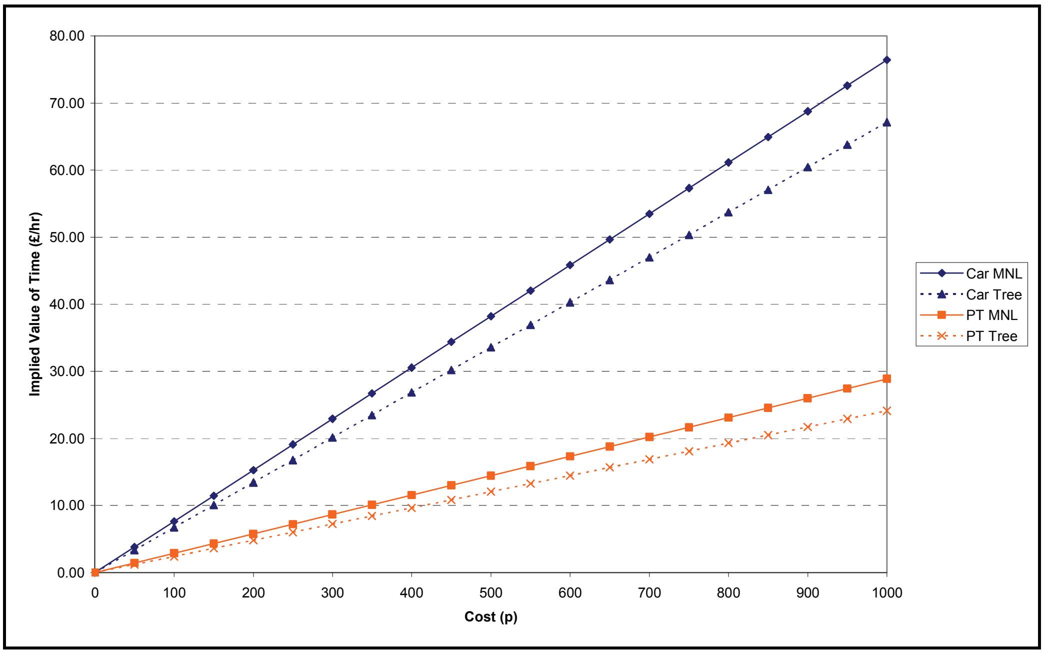
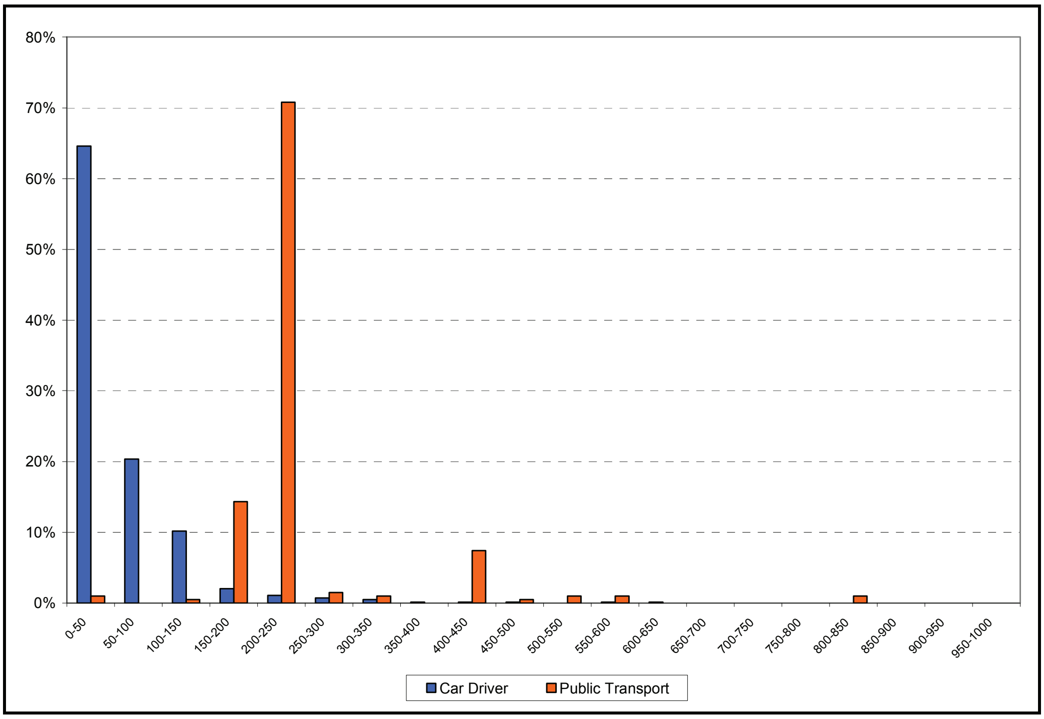


Figure 13: Pooled Other Travel Model Cost Distributions



The other travel model uses a log-cost only formulation and consequently the implied VOT rise in direct proportion to the journey cost. About two-thirds of the observed cost data lies in the 0–50p band, reflecting the short-distance nature of other travel, which equates to implied VOT of between zero and £3.36 per hour. For PT, over 70% of journeys lie in the 200–250p band, which gives VOT of £5–7 per hour. Thus the car VOT are typically lower than the WebTAG average of £4.46 per hour, whereas the PT VOT are slightly higher.

At first glance, the VOT graphs suggest that car VOT are systematically higher than the PT values. However, when the VOT are considered together with the cost distributions for the chosen modes, where mean costs for PT are substantially higher, the VOT for typical journeys are seen to be similar between car and PT and in most cases in line with the WebTAG average values.

8.2 Trip Length Distributions

We compared observed and predicted tour lengths using the unweighted estimation sample from the HI alone, applied using the pooled models – the intercept surveys contain biased trip lengths due to the screenline locations and the higher likelihood of sampling long-distance trips.

Note that the pooled models do not contain destination balancing at the zonal level. However, we used district-level balancing factors.

Figures 14–23 compare car (driver and passenger combined) and PT trip length distributions for the final pooled commute model. They demonstrate a good match to the observed data. It should be noted the predicted trip length distributions are presented both for MNL and modes and above destination structures, and that they two distributions are very similar in most cases, so that the MNL distribution (shown in green) is frequently hidden beneath the modes above destinations distribution (shown in red).

Figure 14: Commute Car Tour Length Distribution

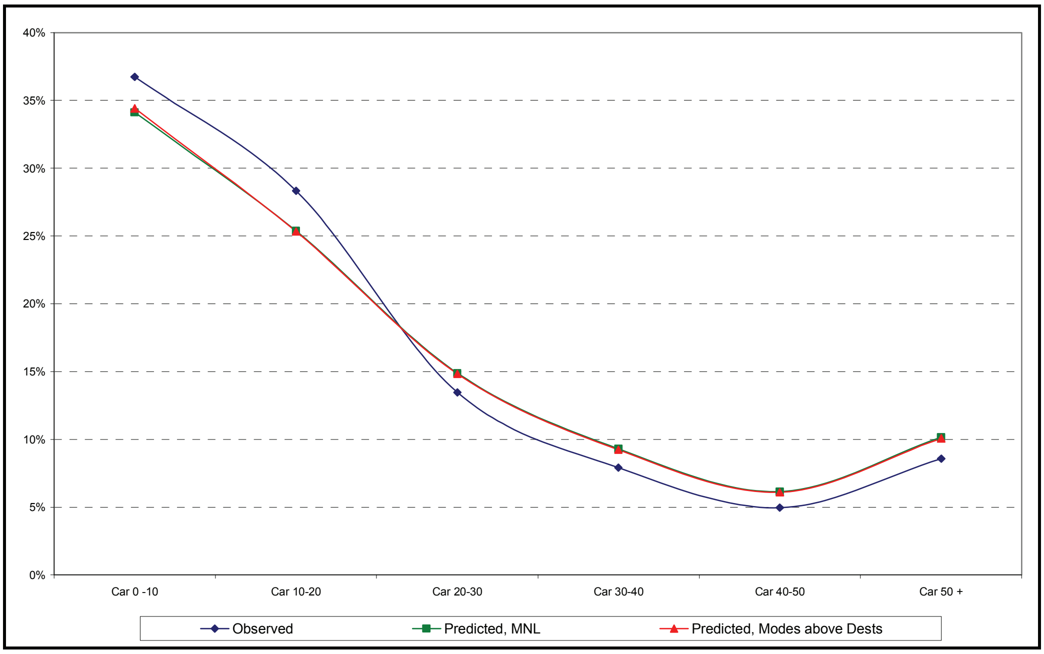
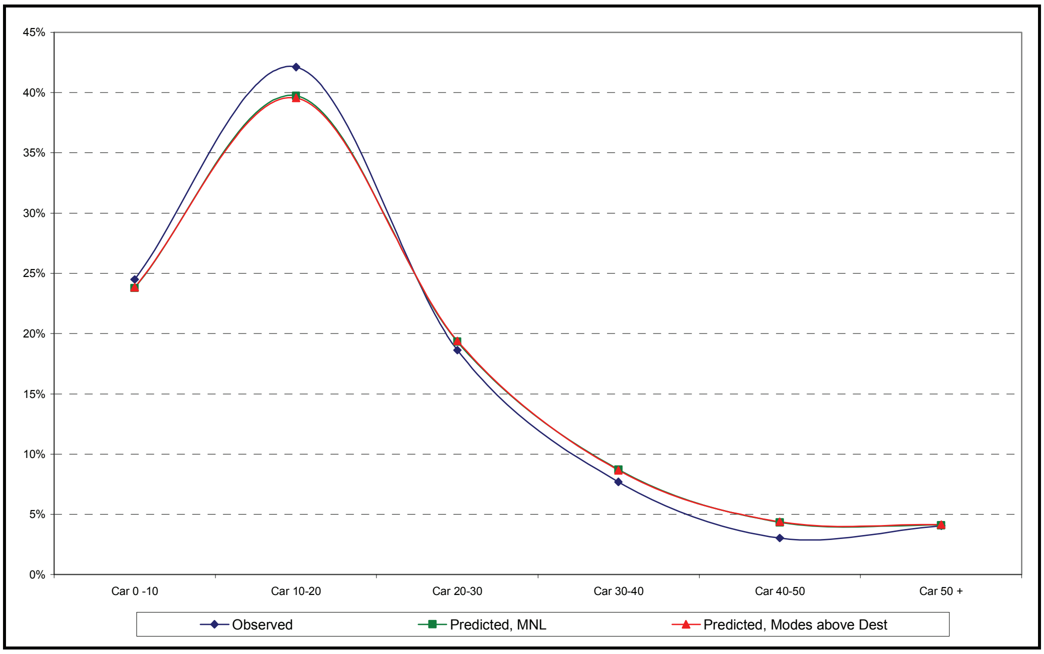


Figure 15: Commute PT Tour Length Distribution



The commute model reproduces the observed distributions well; in particular the dip in the PT distribution for short trips made unattractive by proportionately high out-of-vehicle time is closely matched. For car there is a slight under-prediction of tours in the 0–10 km and 10–20 km bands.

Figure 16: Business Car Tour Length Distributions

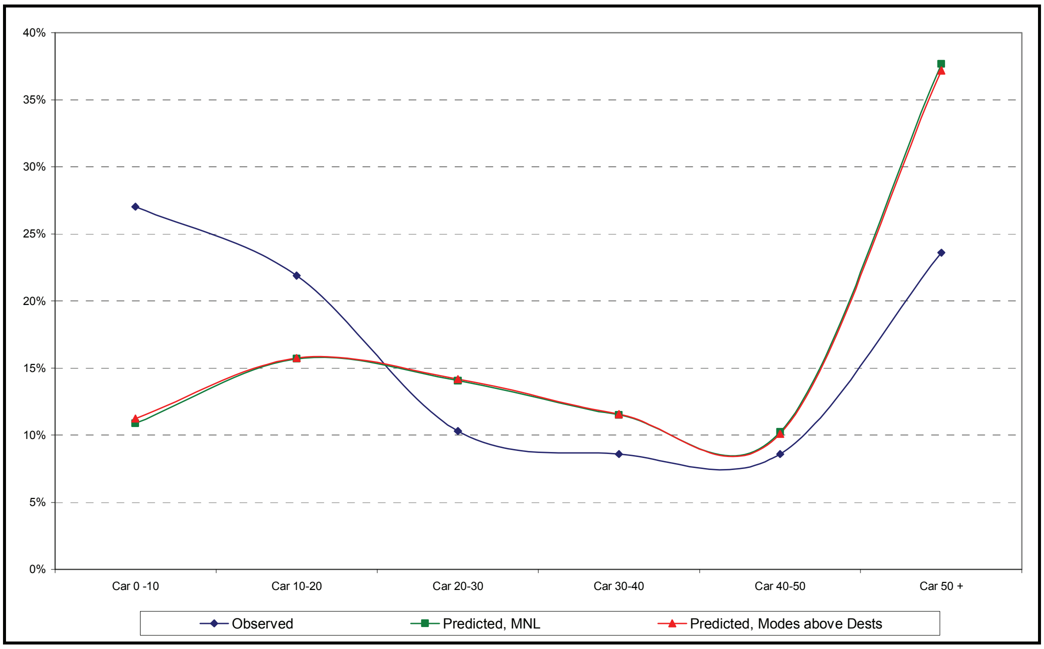
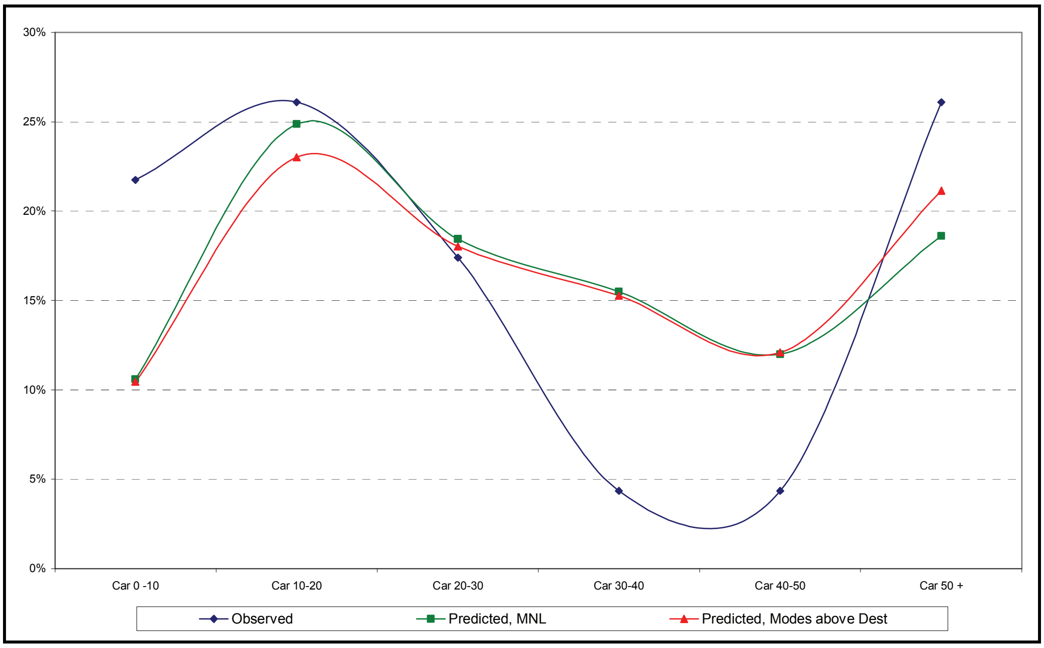


Figure 17: Business PT Tour Length Distributions



For car, the employer's business model significantly underpredicts short tours. Short PT tours are also underpredicted.

Figure 18: Education Car Tour Length Distributions

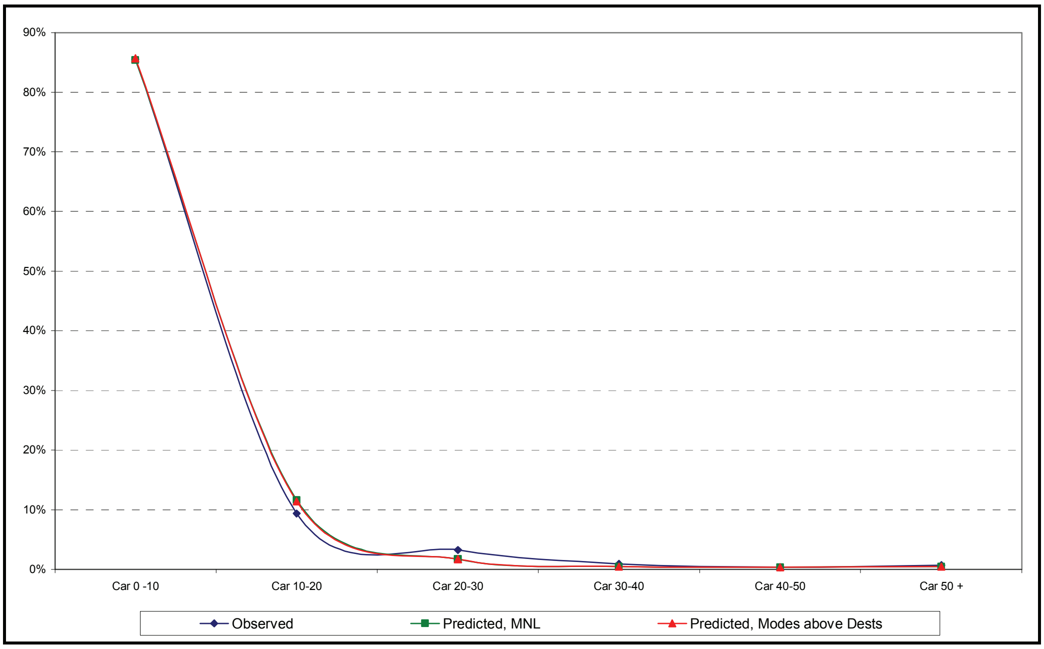
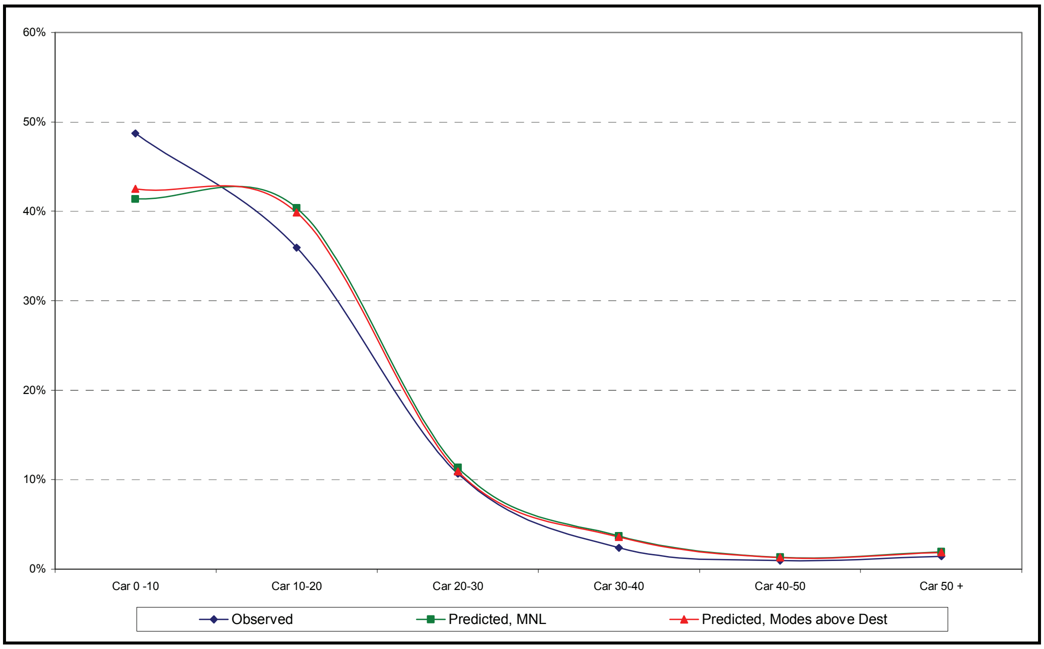


Figure 19: Education PT Tour Length Distributions



In the education model the match with the observed distribution is excellent for car. For PT, there is some underprediction of short distance trips but the fit otherwise is good.

Figure 20: Shopping Car Tour Length Distributions

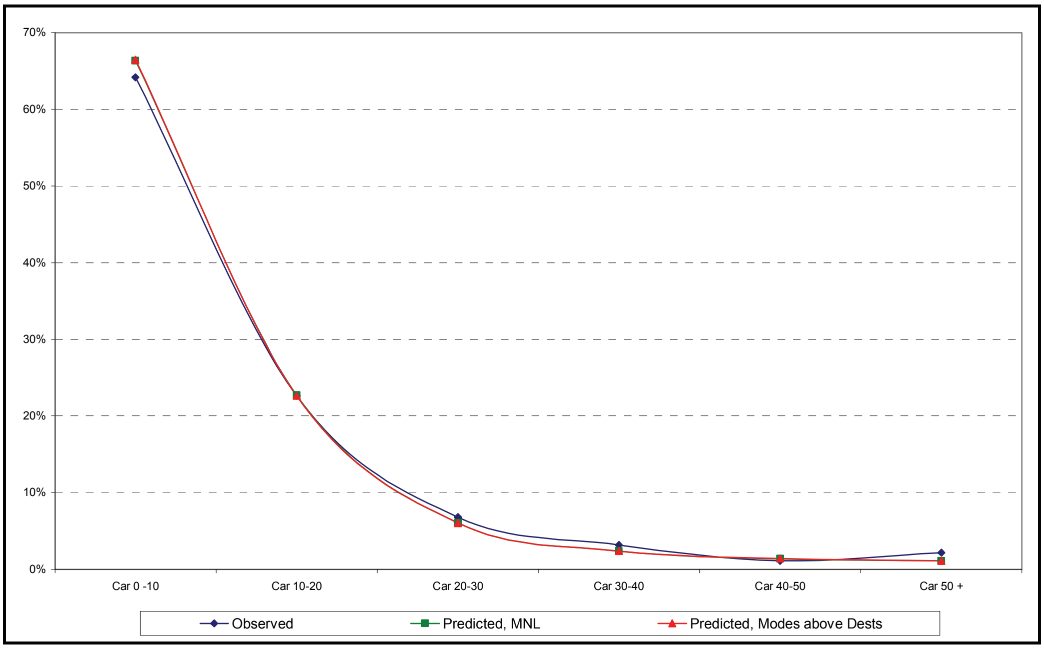
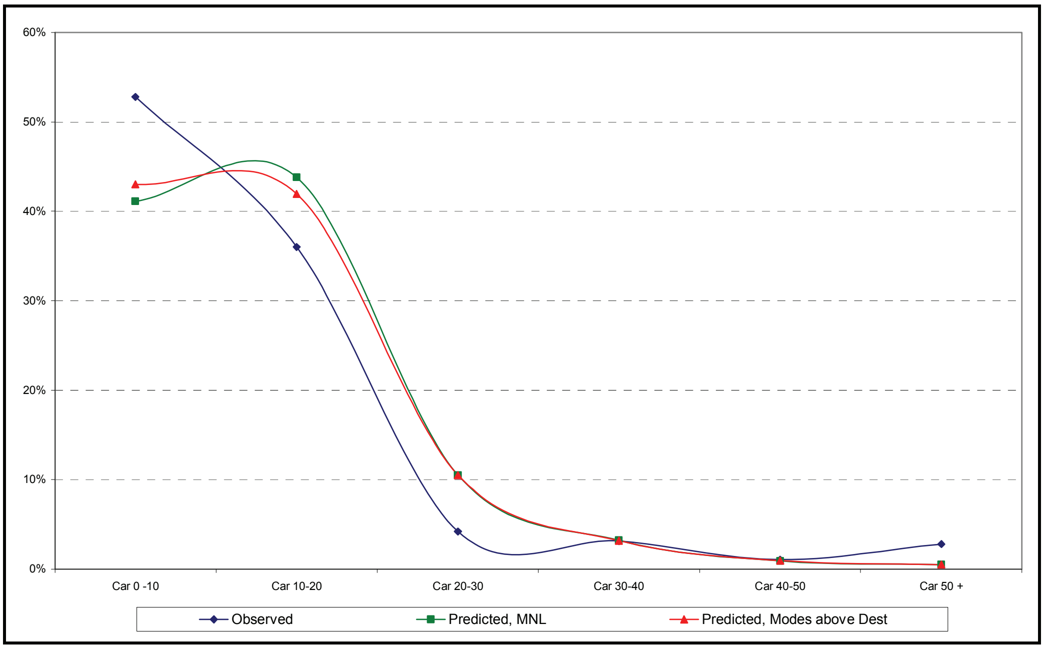


Figure 21: Shopping PT Tour Length Distributions



In the shopping model, for car the match to the observed distribution is again excellent. For PT there is again some underprediction of short distance trips.

Figure 22: Other Travel Car Tour Length Distributions

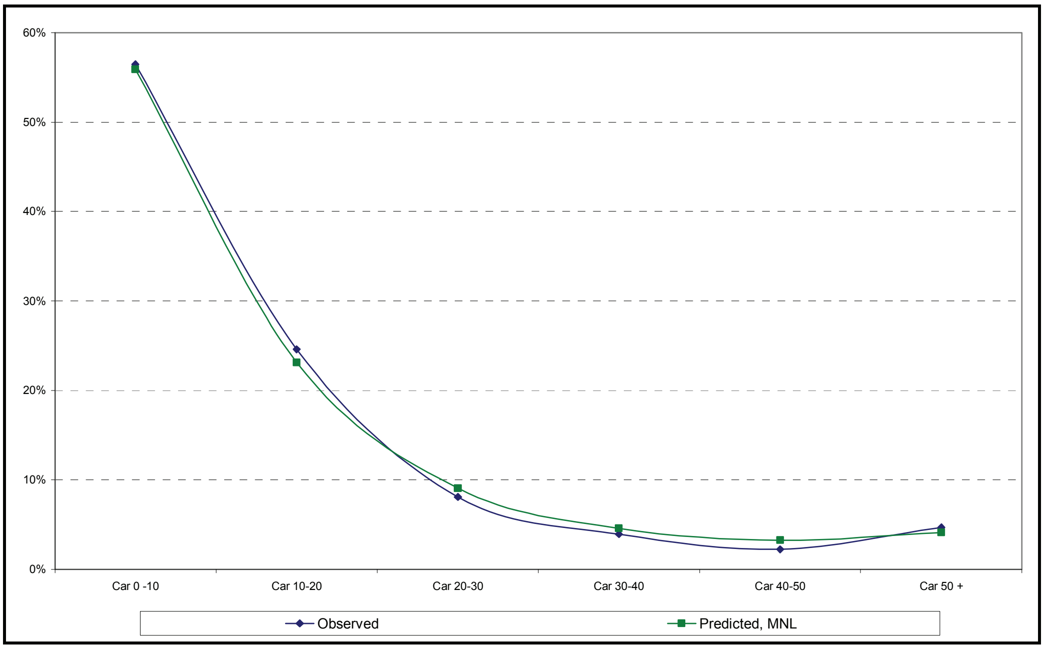
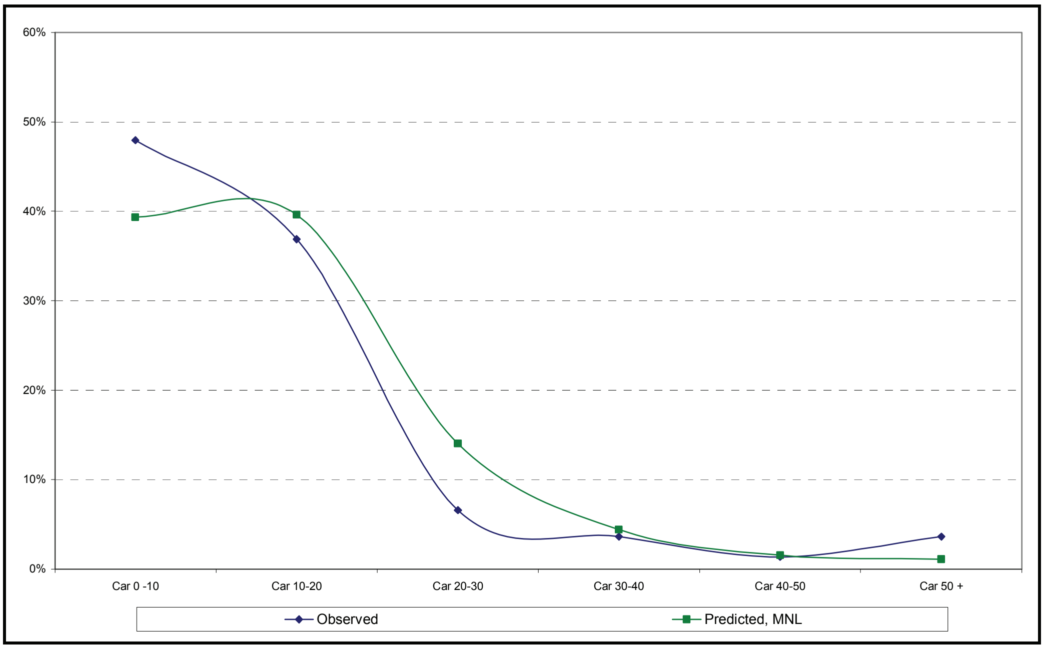


Figure 23: Other Travel PT Tour Length Distributions



For the other travel model the pattern is the same as for education and shopping, an excellent fit for car, some underprediction of short trips for PT.

8.3 Elasticities

Direct car cost kilometrage elasticities for driver and passenger are summarised in Table 38. These are generated by applying the models to the HI samples, with each observation given a weight of 1.

The car cost elasticities are generated by applying a uniform 10% increase to all car costs, that is, both fuel and parking costs and, in the case of business, non-fuel costs as well. The car time elasticities are generated by applying a uniform 10% increase to all car times.

Table 38: Car Cost Kilometrage Elasticities

Purpose	Car Driver		Car Passenger	
	MNL	Nested	MNL	Nested
Commute	-0.36	-0.31	-0.26	-0.18
Business	-0.19	-0.16	0.12	0.03
Education	-0.33	-0.26	-0.19	-0.12
Shopping	-0.29	-0.19	-0.26	-0.10
Other Travel	-0.13	n/a	-0.27	n/a

Table 39: Car Time Kilometrage Elasticities

Purpose	Car Driver		Car Passenger	
	MNL	Nested	MNL	Nested
Commute	-0.67	-0.67	-0.61	-0.50
Business	-0.27	-0.21	-0.11	-0.10
Education	-1.74	-1.57	-1.26	-1.01
Shopping	-1.28	-1.12	-1.44	-1.08
Other Travel	-1.56	n/a	-1.59	n/a

The car cost kilometrage values (Table 39) are reasonable and in line with exogenous sources. For example, WebTAG Unit 3.10.4, Section 1.6, quotes an overall fuel cost elasticity of -0.3, with a range -0.1 to -0.4, with employer's business at the lower end and more discretionary purposes at the higher end. The low elasticity of other travel reflects the fact that this model is log-cost only, which dampens the impact of changes in costs for long-distance tours.

The car time elasticities for education, shopping and other travel are high, and imply that significant increases in kilometrage could result in the savings in travel time provided by the scheme.

The low cost elasticity for other travel had implications when the MNL model was used to predict the impact of the M60 completion scheme. Because of this, we also obtained elasticities for the HI-only model for other travel, which has both linear and log-cost terms (see Table 40).

Table 40: HI Other Travel Kilometrage Elasticities

Elasticity	Car Driver		Car Passenger	
	MNL	Nested	MNL	Nested
Car Cost	-0.36	-0.25	-0.33	-0.15
Car Time	-1.59	-1.35	-1.78	-1.35

It can be seen that the HI-only model, with both linear and log-cost terms, has significantly higher car cost elasticities but lower car time elasticities. The higher car cost elasticity is more consistent with the range of values quoted in WebTAG.

The combined linear and log-cost formulation gives higher cost elasticities than the log-cost only formulation. For other travel, these higher elasticities are closer to the range of values quoted in WebTAG.

8.4 Final Models

The validation of trip lengths revealed little difference between the MNL and tree models, and with the exception of business the implied VOTs also showed only slight differences. The tree models fit the observed data better and are generally somewhat less elastic, with more plausible car time elasticities than the MNL models. We therefore selected the tree models as the final models, except for other travel, where one of the structural parameters was neither significant nor plausible.

This means that final model structures are:

- commute – modes above destinations
- business – modes above destinations
- education – modes above destinations
- shopping – modes above time periods above destinations
- other travel – multinomial modes, time periods and destinations

CHAPTER 9 **Frequency Models**

Frequency models were estimated from the 2002 household interview (HI) data. These models were only estimated for two of the five home-based tour purposes, commuting and home-based other – the two purposes for which we undertook the analysis to predict the before and after cases.

The frequency models can predict the numbers of tours in the before and after cases as a function of the population by socio-economic segment and accessibility. For each purpose the models predict the number of full tours an individual makes on a week day.

Section 9.1 summarises the estimation structure used for the frequency models. In Sections 9.2 and 9.3 we present the results for commuting and other travel.

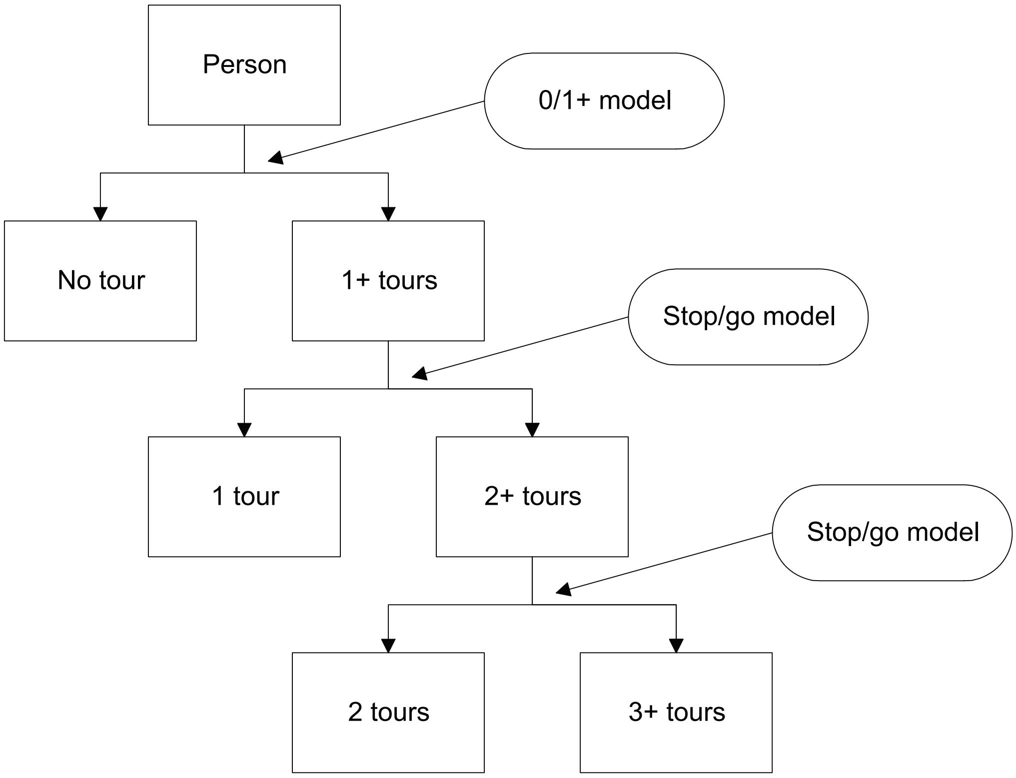
9.1 Model Structure

To model tour frequency we used two linked sub-models.

- The first sub-model is a zero/one plus (0/1+) model that predicts the probability that an individual will make any tours, that is, the model predicts whether an individual participates in an activity.
- The second sub-model is a stop/go model that predicts the numbers of tours an individual will make given that they make at least one tour, that is, the model predicts the level of activity participation.

The model structure is illustrated in Figure 24.

Figure 24: Tour Frequency Model Structure



In the 0/1+ model, utilities are defined for the ‘no tours’ alternative and so the model terms reflect the increased probability of *not* making a tour. Negative model terms therefore imply an increased probability of making a tour.

In the stop/go model utilities are defined for the stop alternatives (one tour, two tours) and so the model terms reflect the probability of *not* making additional tours. This means that negative model terms imply an increased probability of making multiple tours.

A structural parameter, Theta, links the models at each stage. However, the default is to estimate the model with this parameter constrained as zero, which means that at each level the utilities, and hence the predicted choices, are independent of those of the level beneath.

9.2 Commute

The commute frequency model was estimated from the sample of 7,412 workers in the HI data. These workers were observed to make a total of 3,827 full tours, giving a mean tour frequency rate of 0.52 commuter tours per week day.

For the commute model, logsum accessibility measures were taken from the final pooled commute model with destinations above modes. The effects of adding logsum terms to the frequency model are shown in Table 41.

Table 41: Commute Frequency Model Results

File	Com_15M1.F12		Com_15M1_LS.F12	
Converged	True		True	
Observations	7412		7412	
Final log (L)	-5595.3		-5593.0	
D.O.F.	7		9	
Rho²(0)	0.531		0.531	
Rho²(c)	0.009		0.009	
Prepared	17 Sep 08		10 Nov 08	
Estimated	17 Sep 08		10 Nov 08	
Scaling	1.0000		1.0000	
Parameters on Zero Tours:				
none	0.248	(3.3)	0.131	(1.0)
incsegc2	0.279	(5.1)	0.284	(5.2)
female	-0.203	(-3.9)	-0.197	(-3.8)
hhsize1	0.328	(3.5)	0.321	(3.4)
agegt45	0.175	(3.6)	0.172	(3.6)
ft_work	-0.399	(-6.1)	-0.405	(-6.2)
zero_lsum			0.0255	(1.2)
Parameters on Stop:				
stop	3.49	(36.6)	2.79	(7.0)
stop_lsum			0.154	(1.8)
Structural Parameter:				
theta	0	(*)	0	(*)

The logsum terms are both insignificant at a 95% confidence level and their signs are counter-intuitive, as both terms imply higher accessibility results in lower levels of tour making. Therefore COM_15M1, without accessibility terms, was selected as the final model. The terms in the models are defined in Table 42.

Table 42: Commute Frequency Model Terms

Parameter	Definition
none	Constant on zero tours
incseg2	Occupation types C2 and missing more likely to make zero tours
female	Females less likely to make zero tours
hhsize1	Individuals living alone more likely to make zero tours
agegt45	Individuals aged over 45 more likely to make zero tours
ft_work	Full-time workers less likely to make zero tours
Zero_lsum	Logsum term on zero tours
stop	Constant on stop alternatives
stop_lsum	Logsum term on stop alternatives

9.3 Other Travel

We estimated the other travel frequency model from the sample of 19,863 individuals aged five and above in the HI data. These individuals were observed to make a total of 4,791 full tours, giving a mean tour frequency rate of 0.24 other travel tours per week day.

The preferred other travel model for implementation was revised from the final pooled model specification (log-cost only, multinomial mode-destination-time periods) to the final HI model specification (linear and log-cost, modes above time periods above destinations) on the basis that the model elasticities in the final HI model were more acceptable. The frequency models presented here take logsums from the final HI model specification, as this was the model used to make before and after predictions of other travel.

Table 43: Other Travel Frequency Model Results

File	Other_33.F12		Other_33_LS.F12	
Title	MMB		MMB	
Converged	True		True	
Observations	19839		19839	
Final log (L)	-11780.2		-11696.4	
D.O.F.	10		12	
Rho²(0)	0.669		0.671	
Rho²(c)	0.030		0.037	
Prepared	10 Nov 08		14 Oct 08	
Estimated	10 Nov 08		14 Oct 08	
Scaling	1.0000		1.0000	
Parameters on Zero Tours:				
none	0.884	(20.9)	2.22	(12.7)
segc1	-0.252	(-4.9)	-0.230	(-4.5)
hhsize5	0.685	(6.3)	0.650	(6.0)
nocar	0.334	(7.7)	0.135	(2.7)
ft_worker	0.843	(14.5)	0.950	(15.9)
pt_worker	0.408	(5.2)	0.469	(5.9)
student	1.02	(15.8)	0.842	(12.3)
retire	-0.350	(-5.2)	-0.269	(-3.9)
age65	0.314	(4.8)	0.289	(4.4)
zero_lsum			-0.310	(-7.9)
Parameters on Stop:				
stop	1.68	(42.4)	4.69	(14.8)
stop_lsum			-0.683	(-9.8)
Structural Parameter:				
theta	0	(*)	0	(*)

As Table 43 shows, in contrast to the commute frequency model, both logsum terms are strongly significant and have the expected negative sign, that is, improved accessibility results in higher tour frequency rates. Therefore Other_33_LS was selected as the final model.

> For other travel there is evidence that improving accessibility leads to an increase in the total volume of travel.

The model terms are defined in Table 44.

Table 44: Other Travel Frequency Model Terms

Parameter	Definition
none	Constant on zero tours
segc1	Occupation types C1 less likely to make zero tours
hhsize5	Persons in hh more than 5 in size more likely to make zero tours
nocar	Individuals in no car households more likely to make zero tours
ftworker	Full-time workers more likely to make zero tours[10]
ptworker	Part-time workers more likely to make zero tours[10]
student	Students more likely to make zero tours[10]
Retire	Retired persons less likely to make zero tours[10]
age65	Persons aged 65-plus more likely to make zero tours
Zero_lsum	Logsum term on zero tours
stop	Constant on stop alternatives
stop_lsum	Logsum term on stop alternatives

10 Relative to unemployed, looking after home, sick/disabled, other, n/a.

Note that most retired people are aged 65-plus, so both the 'retire' and 'age65' terms are applied, giving a combined effect of -0.036 utility units. The implication is that younger retirees make more travel than those aged 65 and over.

CHAPTER 10 Freight Models

10.1 Model Specification

We distinguished two freight purposes by vehicle type:

- light goods vehicles (LGVs)
- other goods vehicles (OGVs).

These two purposes were modelled separately to reflect the different distribution patterns observed for the two vehicle types. For the LGV category, some trips for non-freight purposes are included in the data, that is, the models predict distribution patterns for all LGV trips. About 25% of LGV trips were for personal business, rather than freight, purposes.[11]

The RSI data do not allow clear identification of the logistics behind the observed vehicle movement. Thus it is not clear whether goods are being transported from the vehicle's home depot to the point of delivery, whether the vehicle is returning empty from a delivery, whether the trip is part of a tour, and indeed whether the primary purpose is to take the driver or a passenger from once place to another. The attribution of causality is therefore somewhat tenuous. As a result, we developed both origin and destination choice models in parallel to assess the impact the directional assumption has on the model results.

The utility of each destination time period alternatives is similar to that used for the (passenger) RSI models:

$$\boxed{V_{d,tp} = \log(A_d) + \lambda\left(\beta_d + \beta_{tp} + \beta_{Cost}Cost_{d,tp} + \beta_{Time}Time_{d,tp}\right)} \qquad (10.1)$$

where: A_d is the attraction variable (total employment)

λ is the scale parameter 'CDBefore' (estimated relative to the after data), defined in Section 4.3.4

β_d is the destination constant, with Manchester specified as the base area

β_{tp} is the time period constant, with separate constants for outward and return trips; in both cases the AM-peak is the base

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11 It should be noted that the RSI passenger models only include car vehicle types, i.e. LGV personal business trips are not double-counted.

β_{Cost}, β_{Time} are the LOS parameters estimated

$Cost_{d,tp}$ is calculated from WebTAG using time and distance skims, plus parking costs

$Time_{d,tp}$ is taken from the distance skims.

The probability of choosing a given alternative is then determined from the standard logit formula:

$$\boxed{P_{d,tp} = \frac{\exp(V_{d,tp})}{\sum_{D}\sum_{TP}\exp(V_{d,tp})}} \qquad (10.2)$$

The probabilities $P_{d,tp}$ sum to unity over the 1,677 destination-time period alternatives.

As per the passenger RSI models, destination alternatives are only available if the probability of crossing a screenline is 0.5 or higher, according to the screenline assignments.

10.2 Model Results

Model results for the different models tested are presented in Appendix H. In this section we summarise the key findings.

We tested models with both linear and log-cost terms. However, for both LGV and OGV this resulted in a positive out-of-vehicle time parameter in the destination choice models. Therefore the linear and log-cost formulation was not selected for the final models.

The values-of-time (VOT) obtained from a linear-cost model are compared with the values given in WebTAG in Table 45.

Table 45: Freight Implied Values-of-Time, £/hr

Model	Implied VOT (t-ratio)	WebTAG
LGV, destination choice	2.88 (10.3)	11.55
LGV, origin choice	4.52 (12.4)	11.55
OGV, destination choice	10.70 (6.0)	10.18
OGV, origin choice	10.90 (7.9)	10.18

The LGV VOT are substantially lower than those quoted in WebTAG. By contrast, the OGV values match the WebTAG values closely.

Structural tests were run for the linear cost models, to assess the relative levels of error in time period and destination choices. The results for a structure with time periods above destinations are summarised in Table 46. The values in brackets give the r-ratios with respect to zero and one)

Table 46: Freight Structural Tests

Model	Structural Parameter (t-ratio)
LGV, destination choice	0.140 (1.4, 8.6)
LGV, origin choice	0.214 (2.0, 7.4)
OGV, destination choice	0.330 (2.2, 4.5)
OGV, origin choice	0.004 (1.6, 398.4)

These results imply that the level of error in time period choice is substantially higher than that in destination choice, a finding consistent with the passenger RSI models we reported in Section 5.2.1. However, the significance of the structural parameters is weak and therefore we decided to retain a multinomial structure in the final models, with destinations and time periods at the same level.

Based on the results from the VOT analysis we decided that the VOT should be constrained to the WebTAG values for both LGV and OGV for the final models. We achieved this by using a generalised time formulation, with costs converted into generalised time units using the WebTAG VOT.

10.3 Validation

To validate the generalised time models, we compared observed and predicted trip length distributions and ran elasticity tests.

Figures 25–28 compare observed and predicted trip length distributions. Observed distributions are presented both weighted and unweighted, to assess the impact the weighting has on the observed distribution. The unweighted distribution gives equal weight to each trip; the weighted distribution assigns a weight depending on the probability of crossing a screenline and the probability of being surveyed at the screenline. Predicted distributions are plotted both with the availability condition used in estimation, where short trips that do not cross a screenline are set unavailable, and with unrestricted availability, which is how the model should properly be applied.

Figure 25: LGV Destination Choice Trip Length Validation

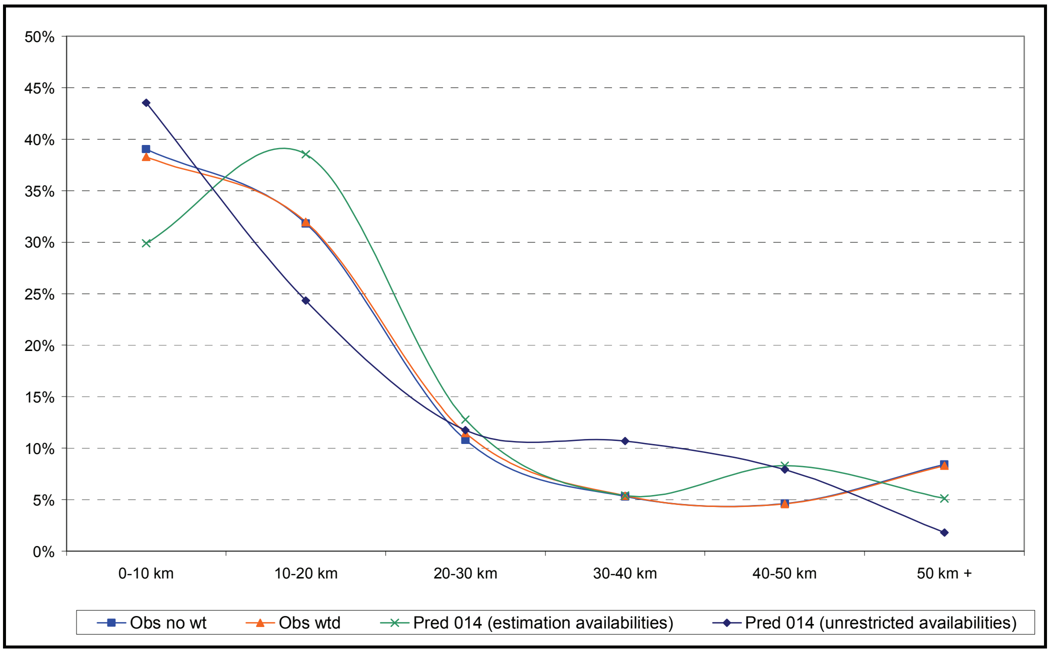


Figure 26: LGV Origin Choice Trip Length Validation

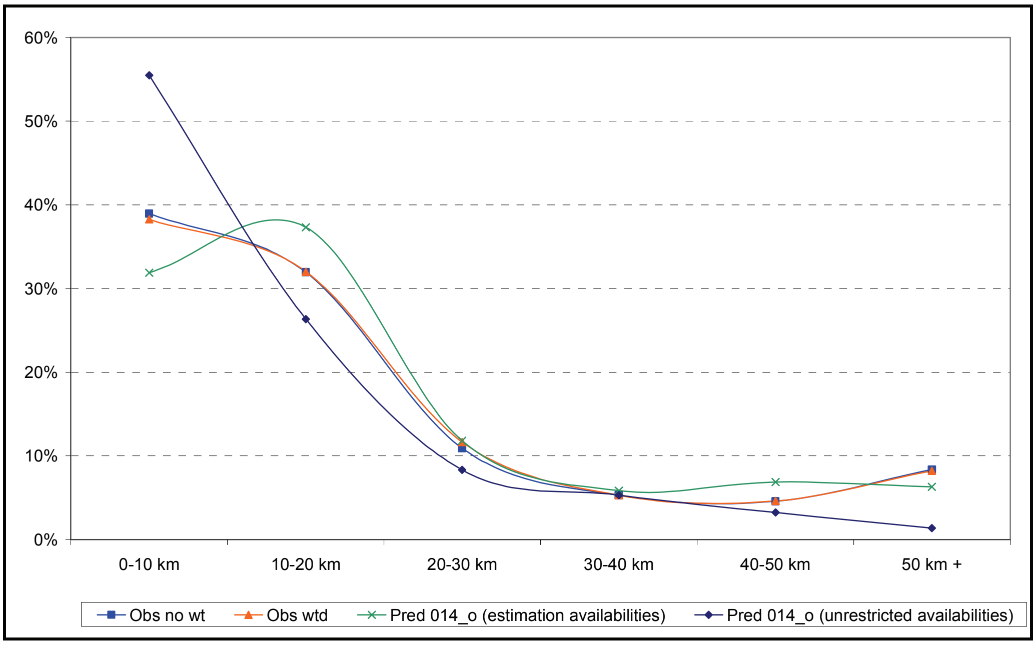


Figure 27: OGV Destination Choice Trip Length Validation

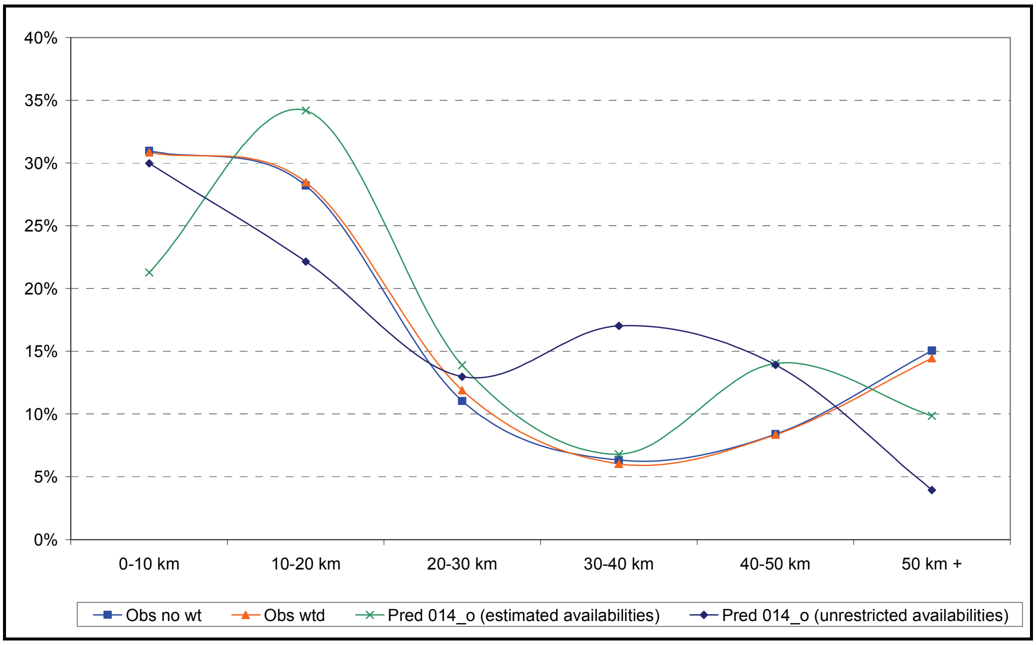
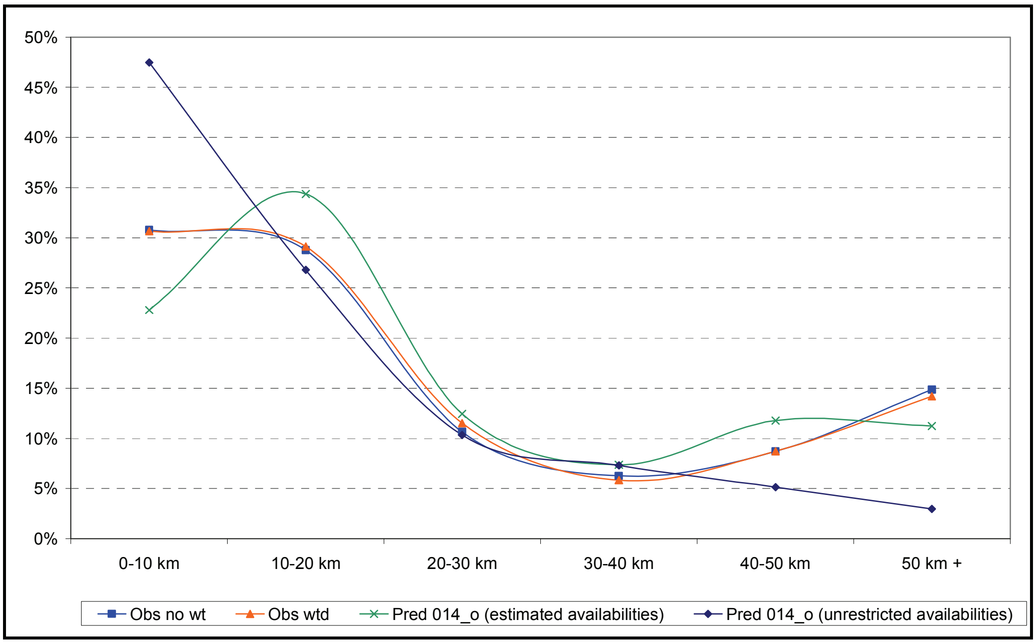


Figure 28: OGV Origin Choice Trip Length Validation



Comparing the two sets of observed distributions reveals that the impact of the weighting is slight. For the predicted distributions it can be seen that with unrestricted availability, a significantly increased proportion of short-distance trips is predicted in three of the four comparisons. Thus the under-sampling of short-distance trips is compensated for. However, this does not occur in the OGV destination choice model and the reasons for this are not clear.

We made cost elasticity runs by increasing all costs (fuel plus non-fuel) by a uniform 10% and similarly made time elasticity runs by increasing all times by a uniform 10%.

The results are compared to exogenous sources in Table 47.

Table 47: Freight Elasticity Validation

Model	Cost Elasticity	Time Elasticity
LGV, destination choice	-0.40	-0.41
LGV, origin choice	-0.22	-0.26
OGV, destination choice	-0.47	-0.19
OGV, origin choice	-0.27	-0.14
Bradburn and Hyman	-0.25	
Belgian Model	-0.95	-0.73
Norwegian Model	-1.01	-0.09
Swedish Model	-0.4	-0.63
SCENES EU Model	-0.62	

The Bradburn and Hyman analysis reported above is based on fuel sales and therefore covers all behavioural reactions, such as changes in the fleet, and not just origin and destination choice.

The effect of road transport cost on road tonne-kilometres is substantially higher than the Bradburn and Hyman figure, according to all four sources in de Jong (2003); however, these effects derive from mode choice only in the case of SCENES (where the distribution effect is stated to be small). Moreover, unlike our figures, the de Jong results are based on full equilibration. On balance, it might be said that our models are more elastic than previous information would indicate, though given the wide range of values the evidence is not entirely clear.

There is a difference between the origin and destination choice models, with destination choice models consistently producing higher elasticities for cost, more consistent with the international sources.

CHAPTER 11 Estimation Summary

This chapter summarises the key findings from the model estimations.

11.1 Intercept Results

11.1.1 Road Side Interview Models

Models of destination and time period choice were developed from before (1999) and after (2003) road side interview (RSI) data. These models had reasonable implied values of time (VOTs) for commute and non-home-based (NHB) business, but values that were either low or high for other model purposes.

It was concluded that it was not possible to model time period choice using the RSI data.

The longitudinal test only converged for one the six model purposes. However, the values when the models failed suggest that travellers making choices in the after case may be responding to an average of before and after conditions, rather than after conditions alone, with greater weight given to after conditions as would be expected.

11.1.2 Public Transport Interview Models

Models of destination and time period choice were also developed from before (1999) and after (2003) public transport interview (PTI) data. These models yielded reasonable values of time for shopping, but either low or high values for all other model purposes.

The valuations of wait time and access and egress time were generally low, with values often just over one, and in some cases under one.

In contrast to the RSI data, it was possible to identify structures with destination and time period choice from the public PTI data, and so it was concluded that the data did provide some information on time period choice.

There was little evidence for longitudinal effects.

11.1.3 Pooled Intercept Models

The RSI and PTI datasets were pooled together, and structural tests undertaken to investigate whether mode (car versus public transport), time period and destination choices could be represented. These tests concluded that the data did not support modelling mode choice for any of the model purposes, and that only for shopping did the data support the modelling of time period choice. Therefore, with the exception of shopping, the intercept data was only used to model destination choice.

The structural test for shopping yielded a structure with destinations beneath time periods.

The implied VOTs were reasonable for commute, low for business purposes, and high for the other model purposes.

Only one of the longitudinal tests converged, however the results at the point of failure again suggest that travellers making choices in the after case may be responding to an average of before and after conditions, rather than after conditions alone, with greater weight given to after conditions.

11.2 Household Interview Results

Household interview models were developed for the five home based purposes (commute, business, education, shopping and other). Non-home-based models were not developed from the household interview data. The models included mode, destination and time period choices. Five modes (car driver, car passenger, PT, walk and cycle) were modelled.

Tests demonstrated an improved fit to the data when it was assumed that car costs were shared between drivers and passengers. The best fit to the data was obtained by assuming different degrees of cost sharing for different purposes, with no cost sharing at all for employer's business, and full cost sharing (i.e. each passenger pays the same as the driver) for other travel.

Consistent with the findings from the pooled PTI models, the valuations of access and egress time and wait time were low in the household interview models. It was hypothesised that this finding might imply that the PT level of service (LOS) did not provide a good measure of the actual access egress and wait times faced by travellers in the household interview.

A number of car availability variables were identified in the models, that reflect the higher probability of travelling as a car driver or car passenger in households with higher levels of car availability. A number of socio-economic terms were also identified to reflect variations in mode preferences by socio-economic group, gender, working status and age.

Structural tests were undertaken to investigate the relative sensitivity of mode, destination and time period choices. For mandatory purposes (commute, business and education) these tests concluded that the household interview data provides little information on (macro) time period choice, and so time period choice should be dropped from the structure, and that a structure with modes above destinations gives the best fit to the data. For discretionary purposes (shopping, other) the best structure had modes above time periods above destinations. However, the evidence for this finding is not strong.

No longitudinal tests were run with the household interview data, as it was all collected after the opening of the Manchester Motorway Box.

11.3 Pooled Model Results

The pooled models were estimated by pooling the intercept data with the household interview data. Based on the findings from the intercept models, the intercept data was only used to model destination choice. The household interview data was used to model destination and mode choice for mandatory purposes, and mode, destination and time period choice for discretionary purposes.

Scaling parameters were used in the models to account for different levels of error across the different datasets relative to the household interview data. In most cases, these had values less than one, which is to be expected given that the household interview data records time period information in both directions, and allows the incorporation of variations in preferences with socio-economic characteristics.

Consistent with the findings from the PTI and household interview models, the relative valuations of access and egress time and wait time are low, with values lower than public transport in-vehicle time in the majority of cases.

The structural tests for the mandatory purposes (commute, business, education) confirmed the structures identified from the household interview models, with modes above destinations in each case. The structural test for shopping was also consistent with the household interview model test, with modes above time periods above destinations. However, it was not possible to identify a plausible structure for other travel from the pooled data, and thus a multinomial model structure was adopted. This was inconsistent with the structure identified from the model developed from the household interview data which indicated a structure of modes above time periods and destinations.

The longitudinal tests again did not converge fully, and so should be interpreted with caution. Nonetheless, the results again suggest that travellers making choices in the after case may be responding to an average of before and after conditions, rather than after conditions alone, with greater weight given to after conditions as would be expected.

11.4 Pooled Model Validation

The pooled models were validated by examining the implied VOTs, comparing observed and predicted tour length distributions, and by examining model elasticities.

The commute VOTs are slightly low compared to the values in WebTAG. The business VOTs are substantially higher than the commute values, but not as high as the employer's valuations given in WebTAG. For shopping and education, the VOTs are consistent with the WebTAG values. For other travel, the car VOTs are slightly low, and the PT VOTs slightly high, relative to the WebTAG values.

The comparison of observed and predicted tour length distributions for car revealed an excellent match for all purposes except for business, where short tours are underpredicted by the model. For PT, the match is excellent for commute, and good for other purposes, with a tendency to under-predict short tours.

The fuel cost elasticities were judged to be reasonable in the final models, with the lowest value for business as would be expected. The car time elasticities were also judged to be acceptable.

11.5 Frequency Models

Tour frequency models were developed for commute and other travel. These included a number of socio-economic terms to reflect variations in tour frequency with income, adult status, gender, age and household size.

The impact of increased accessibility, measured as a logsum over modes, destinations and (in the case of other travel) time periods, was tested in the frequency model. No significant effect was identified for commute travel. However, a significant effect was identified for other travel that implies that increases in accessibility will result in slightly higher tour frequency rates.

11.6 Freight Models

Freight models were developed separately for light goods vehicles (LGVs) and other goods vehicles (OGVs). The models predicted the choice of either origin or destination zone, as well as the choice of time period. The results gave no clear indication as to whether it was preference to model origin choice assuming the destination to be fixed, or to model destination choice assuming the origin to be fixed.

The structural tests suggested a structure with time period choice above destination choice. It should be noted that the error in time period choice was substantially higher than the error in destination choice.

Comparison of observed and predicted trip length distributions demonstrated a reasonable match to the observed data.

The elasticity of the models to cost changes seems to be high compared to the available evidence, however the variation in the comparison values is high.

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APPENDICES

Appendix A: Estimation Strategy

In the context in which this report is set, we have a number of datsets to be used to estimate the travel demand models:

- before (B) data, comprising road-side interview (RSI) and PT intercept surveys
- after (A) data, comprising RSIs, PT intercept surveys and household interviews.

In earlier work for this study, MVA (2003) set out four strategies for model estimation using the before and after datasets:

- independent estimation on B and A data
- joint estimation on aggregated data using absolute costs
- joint estimation on aggregated data using differential costs
- joint estimation on disaggregate data using absolute costs.

It might be thought that disaggregate estimation using differential costs was not possible, because records in the B data will often have no corresponding record in the A data (and *vice versa*), but as we discuss in the following section some information of this type can be obtained.

Independent estimation (Strategy I) could use either aggregate or disaggregate data. MVA (2003) argued that the results of this were likely to be confusing. We also preferred an approach using merged data, but proposed tests with each dataset independently (a) to check whether there were specific problems in any of the datasets; and (b) to detect any significant apparent changes in the *behavioural mechanisms* (as distinct from the behaviour). It is in any case agreed that the main work will be done using merged data, that is, not Strategy I.

The arguments in favour of using disaggregate data are that some of the induced components were expected to be small and so, despite the size of the data base, might be difficult to identify. For this reason, the modelling approach made full use of all the variance present in the data by preserving the disaggregate records from the intercept surveys (RSI and PT) and from the HI data. The specific advantages of disaggregate records is that they allow the use of rigorous discrete choice methods, permitting tests of significance and application of confidence limits to coefficient estimates. Used with discrete choice methods, unweighted disaggregate records are the most efficient in terms of giving minimal estimation error. Further, by using records that contain the full range of segmentation available in the data – limited in the case of *intercept* surveys, extensive in the case of *home interviews* – the full benefits of this segmentation were obtained.

Thus for our work, we preferred Strategy IV, rather than either II or III, which require the aggregation of data that would cause loss of information. The investigation of the impact of differential costs over time, which was the basis of the MVA (2003) recommendation to use Strategy III, can be done using a disaggregate approach, with the advantages that flow from disaggregation.

Appendix B: Weighting

Weighting Procedure

The models for this study are estimated on five data sources:

- roadside interviews (RSI), before and after
- public transport interviews (PTI), before and after
- home interviews (HI), after only.

Combination of these surveys for modelling needs to take account of the specific data collection procedures used for each of the surveys, which may introduce specific biases.

The RSI data were collected at two screenlines, at each of which a fraction of the traffic was surveyed for part of the day selected for each screenline site. A key point to note is therefore that there are far more long trips represented in the RSI data than in a representative sample of trips in the study area, because longer trips have a higher chance of crossing one (or even two) of the screenlines. Given that a tour was made, the probability of each leg (outbound and return) of that tour being captured in the RSI data is the product of

- the probability that the choices made make it available for capture, in turn the product of
  - the probability that the tour was made at a time when interviewing was underway
  - the probability of choosing one of the interviewed modes (car driver and car passenger)
  - the probability, given the origin, that a destination was chosen on the other side of the screenline
  - the probability that the route chosen would actually take the tour through the screenline
- and the probability that it was actually captured, among the vehicles passing the screenline.

The choice of mode and time period is predicted by the models estimated. Probabilities of the route actually crossing a screenline (often zero or 1) are taken from assignment results, while the sampling rates at the screenline are taken from data on the surveys conducted; these probabilities are calculated separately for the before and after data.

The sampling probabilities for the PTI are built up in a generally similar way to the RSI, except that separate probability calculations have to be made for bus, metro and train surveys, which are then combined, as public transport is treated as a single mode in the choice models.

For the HI data, interviewing rates were calculated for each zone of the study area based on the fraction of the population that was interviewed. This sampling rate was then applied for all the tours made by each household interviewed in that zone. Normally, when modelling using HI data alone, it is not necessary to use these interviewing rates as this type of 'exogenous' sampling (not related to the choices being modelled) does not cause a bias in the modelling. However, when we wish to combine HI data with data based on endogenous sampling (related to choices), as in this case, these factors are needed.

The theory of modelling using mixed endogenous and exogenous sampling is complex. A small but dense literature deals with the problems, which are very difficult if a general formula is required. In this case we are applying a simplified approach, based on the assumption that the sampling rates are known without error. This assumption seems, in the circumstances and given the fairly large sample sizes, to be reasonable.

With this assumption, a simplification of work by Bierlaire *et al.* (2006) can be used, which tells us that:

$$\boxed{R(i, x,\theta) = Q(i,x).T(x,\theta)} \qquad (A.1)$$

where i represents the choice

x represents exogenous variables

θ represents the unknown parameters in the model

R is the probability an individual with characteristics x making choice i is sampled

Q is the sampling rate for choice i given characteristics x

T depends on x and unknown parameters θ.

That is, the sampling rates are a product of

- a term Q that depends on exogenous variables and the choice only
- a term T that depends on exogenous variables and unknown parameters only.

We can estimate the model without bias by applying weighting factors of 1/Q to each observation. T cancels out in the relevant expression (see Bierlaire *et al* for details). This approach is effectively the same as that derived by Manski and Lerman (1977) in their WESML estimator (weighted exogenous sample maximum likelihood).

Calculation of Q then takes account of the probability that a tour could have been sampled in any of the five datasets: the overall sampling rate is the sum of the rates in each survey as given by equation (3.1).

$$\boxed{Q \propto \phi_{HI} + \phi_{RSI} + \phi_{PT}} \qquad (A.2)$$

where: ϕ_{HI} is the sampling rate in the HI

ϕ_{RSI} is the sampling rate in the RSI, discussed above

ϕ_{PT} is the sampling rate in the PTI, discussed above.

Note that ϕ_{RSI} is zero for any non-car observation, similarly ϕ_{PT} is zero for any non-PT observation. Note also that in the before situation, there is no HI and therefore ϕ_{HI} is zero.

The main complications arise in these calculations because the HI data observe a complete tour, whereas the RSI and PTI surveys observe only one leg of a tour. Apart from affecting the sampling rates in a simple way, the more complicated aspects of this fact are that we do not know the time period of the 'other' leg of a tour in the RSI or PTI data, so that sampling rates have to be calculated as an approximate average of the rates over possible periods of the day. This averaging is performed separately for each travel purpose using observed outward and return time period choice proportions from the HI. Similar problems arise in the actual estimation when we need to know what the appropriate level of service offered by the transport networks would be.

Sampling Rates

As we discussed above, the sampling rate is the product of the chance that a trip is eligible for sampling by crossing a screenline, termed the 'crossing rate',[12] and determined by special 'screenline assignments', and the probability a trip was actually interviewed given it crossed a screenline, termed the 'interview probability'. The weight is then the reciprocal of the sampling rate.

If a record has a low sampling rate it will receive a high weight, and there is therefore a risk that a few records with high weights will bias the estimation. Therefore we undertook analysis of the distribution of crossing rates and sampling probabilities to assess the number of records with low sampling rates and the impact these have on the model results.

Table A1 presents:

- the range of interview probabilities at the intercept sites, that is, the probability of being interviewed at a given site
- the range of the crossing rates given by the screenline assignments
- the total number of screenlines used for each survey
- the total number of observations for each survey
- the distribution of crossing rates for the intercept surveys, calculated by determining the crossing rates from the screenline assignments for the observed OD pairs in the intercept surveys.

[12] 'Rate' is used intentionally instead of probability because the values can be greater than 1 if more than one screenline is crossed.

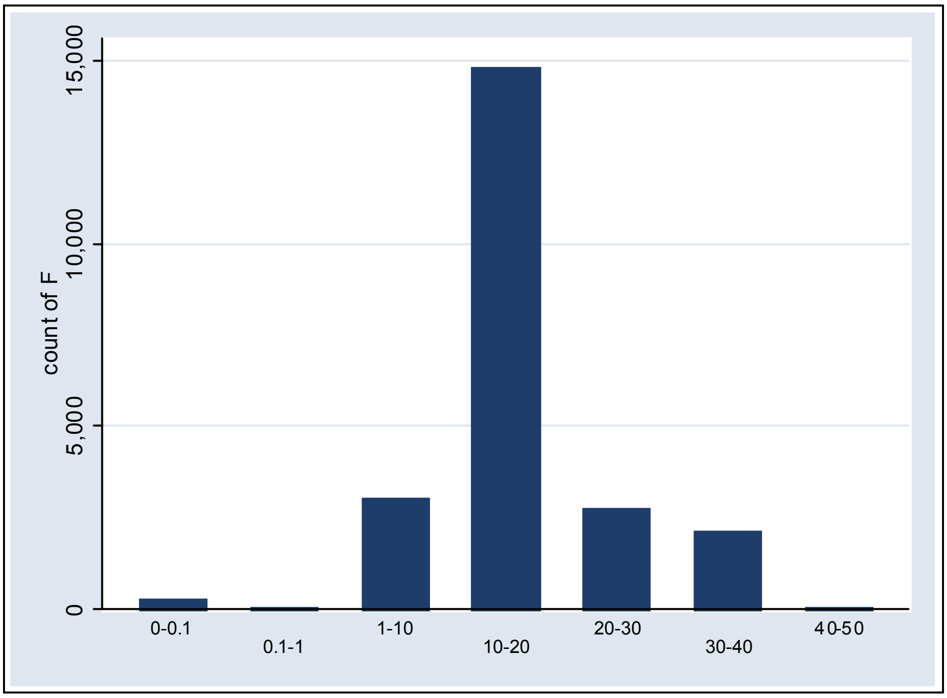
Table A1: Crossing Rate and Sampling Probability Analysis

	RSI before		RSI after		PT before		PTafter	
Interview probabilities		0.119–0.139		0.101–0.143		0.115–0.426		0.201–0.410
Crossing rates		0–2		0–2		0–1		0–1
Number of screenlines		4		4		4		4
Total observations		20,665		27,523		13,704		12,852
Crossing rate zero	2,504	12.1 %	3,444	12.5 %	390	2.8 %	299	2.3 %
0 < crossing rate < 0.001	88	0.4 %	160	0.6 %	18	0.1 %	24	0.2 %
0 < crossing rate < 0.01	676	3.3 %	714	2.6 %	59	0.4 %	67	0.5 %
0 < crossing rate < 0.1	800	3.9 %	920	3.3 %	244	1.8 %	268	2.1 %
0 < crossing rate < 0.5	849	4.1 %	1,034	3.8 %	919	6.7 %	673	5.2 %
0 < crossing rate < 0.99	1,228	5.9 %	1,265	4.8 %	3,342	24.4 %	3,848	29.9 %

As the table shows, the interview probabilities span a relatively restricted range and present few problems, even when inverted as required for weighting. In contrast, the crossing probabilities span a much larger range, fully from zero to 1 in the case of PT, and action needs to be taken to avoid problems in model estimation. It can also be seen in the table that the differences between before and after data are relatively limited, so that procedures can be consistent between the two dates, while differences between PT and RSI data are more marked. In particular, significantly more RSI observations have zero crossing probability according to the screenline assignment.

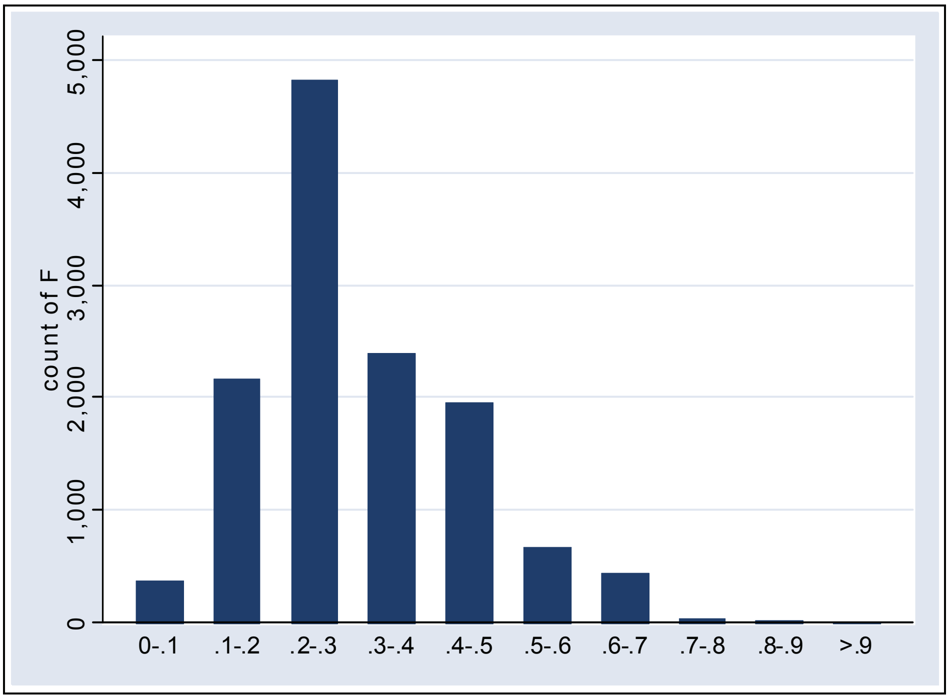
The sampling rate distributions for the RSI and PT before samples are given in Figures A1 and A2.

Figure A1: RSI before Sampling Rate Distribution



Note: the x-axis is the sampling rate multiplied by 100, ie rates from zero to 0.5 are presented.

Figure A2: PT before Sampling Rate Distribution



For the RSI, the cluster of values for rates between 0.1 and 0.2 correspond to interview probabilities in the range 0.1 to 0.2 multiplied by crossing rates of exactly 1; similarly the cluster of PT values in the rate 0.2 to 0.3 corresponds to interview probabilities in the range 0.2 to 0.3 multiplied by crossing rates of exactly 1.

For both RSI and PT, there are a reasonable number of observations where the sampling rates exceed the maximum interview probabilities, which can only happen if the crossing rate exceeds 1, i.e. more than one screenline is crossed. These observations would not be expected to cause a problem in model estimation, as they receive a lower weight. However, there is also a reasonable number of observations with low sampling rates, which could potentially bias the estimation due to the high weights these observations receive.

Crossing Rate Threshold

To investigate the impact of low sampling rate observations further, we ran a series of model estimation runs where crossing probabilities below different thresholds were excluded. The impact of the threshold on the models in terms of the implied values-of-time (VOT) in £/h, and the t-ratios of the cost and in-vehicle-time (IVT) parameters, is summarised in Table A2.

Table A2: RSI Crossing Rate Threshold Runs

Threshold	RSI before			RSI after		
	VOT	Cost	IVT	VOT	Cost	IVT
< 0.001	24.99	14.1	94.8	3.13	51.8	52.2
< 0.01	5.66	22.1	40.5	4.10	34.8	42.3
< 0.1	5.76	22.4	41.0	3.65	35.9	38.3
< 0.5	6.08	21.7	41.8	3.79	35.1	38.9
< 0.99	5.65	22.0	39.5	3.79	35.0	38.7

With a threshold of 0.001, which corresponds to a weight of 1000, the before VOT are unfeasibly high. Other thresholds yield plausible VOT and highly significant cost and time parameters.

The after values of time are plausible, if a little low, for all crossing thresholds, as shown in Table A3.

Table A3: PT Crossing Rate Threshold Runs

Threshold	PT before			PT after		
	VOT	Cost	IVT	VOT	Cost	IVT
< 0.001	2.95	-11.5	-19.3	3.24	27.6	57.6
< 0.01	2.91	-8.4	-14.8	2.43	28.0	429.
< 0.1	2.84	-7.4	-12.6	2.59	21.5	36.2
< 0.5	2.77	-6.1	-10.3	3.13	14.6	32.4
< 0.99	2.61	-5.2	-8.3	2.16	16.5	26.2

In the before runs, the VOT remain reasonable across different thresholds, with some reduction in magnitude as the threshold increases. The cost and in-vehicle time parameters reduce in magnitude as the threshold increases.

On the basis of these analyses, it was decided to proceed with the modelling with a threshold value of 0.5 for both RSI and PT data. We took into account the following points in making this decision:

- the need to exclude observations where route choice was so unlikely there was probably some error in the coding
- the need to exclude observations that would have an undue influence on the estimation (because of their very high weight)
- acceptance of the fact that the assignment process is subject to error
- the need to retain as many data as possible, subject to the considerations above
- the need to ensure that the choice of threshold value did not itself have undue influence on the models
- the need to obtain reasonable estimates of the parameters across all the models
- the wish to maintain consistency between before and after and (to a lesser extent) between RSI and PT data.

The value of 0.5 appears to balance these considerations.

Appendix C: Socio-Economic Classifications

Occupation type:

- AB
- C1
- C2
- DE
- missing

Working status:

- full-time worker, 38+ hours
- full-time worker, 30–37 hours
- part-time worker, 16–30 hours
- part-time worker, less than 16 hours
- retired
- full-time education
- looking after home/family
- unemployed/not working
- permanently sick or disabled
- other (specify)

Age:

- 0–4
- 5–10
- 11–15
- 16–20
- 21+

Appendix D: Guide to Model Results

Appendices E, F and G present results for the final model specifications. In each case, separate tables of model results are presented for each journey purpose. Within a given table, results are generally presented for:

- a multinomial structure, with each choice decision equally sensitive to changes in utility
- a structural test, to assess the relative sensitivity of the different choice decisions
- a longitudinal test, using the multinomial structure.

The tables of results group the model parameters into the following categories:

- cost parameters
- level-of-service parameters (presented together with cost for the intercept models) for times, distances and numbers of transfers
- car availability parameters
- socio-economic parameters
- mode-specific constants
- intrazonal constants
- destination constants
- time period constants
- attraction terms
- structural parameters.

Model parameters are presented together with their associated t-ratios in brackets (the parameter estimate divided by its standard error). In general parameters are only retained in the models if the estimate has a t-ratio of 1.96 or higher, indicating the parameter to be statistically significant at a 95% confidence level.

The DOF is the number of parameters estimated in the model.

Appendix E: Intercept Models

Roadside-Interview Models

Not all of the models presented in this section have converged, the second row in each table of model results clarifies whether the model in question has converged.

Model Exclusions

	Commute		Business		Education	
Total observations	73,390	100.0%	8,395	100.0%	4,220	100.0%
Car passenger observations	7,373	10.0%	770	9.2%	1,677	39.7%
No attraction variable in dest zone					636	15.1%
Imputed records	8,420	11.5%	996	11.9%	333	7.9%
Off-peak records	3,213	4.4%	263	3.1%	40	0.9%
Screenline crossing prob = zero	5,948	8.1%	933	11.1%	210	5.0%
Sline crossing prob >0 and < 0.5	1,883	2.6%	244	2.9%	57	1.4%
Estimation sample	46,553	63.4%	5,189	61.8%	1,267	30.0%

	Home-Shopping		Home-Other Travel	
Total observations	24,879	100.0%	49,229	100.0%
Car passenger observations	8,939	35.9%	14,068	28.6%
Imputed records	1,540	6.2%	3,756	7.6%
Off-peak records	430	1.7%	2,040	4.1%
Screenline crossing prob = zero	2,359	9.5%	4,494	9.1%
Sline crossing prob >0 and < 0.5	475	1.9%	955	1.9%
Estimation sample	11,136	44.8%	23,916	48.6%

	NHB Business		NHB Other	
Total observations	12,387	100.0%	27,265	100.0%
Imputed records	1,496	12.1%	3,008	11.0%
Off-peak records	99	0.8%	730	2.7%
Screenline crossing prob = zero	1,711	13.8%	3,842	14.1%
Sline crossing prob >0 and < 0.5	362	2.9%	751	2.8%
Estimation sample	8,719	70.4%	18,934	69.4%

Note that for the non-home-based purposes no attempt was made to infer the purposes of passengers and so there are no car passenger observation exclusions.

Commute

	MNL		Structural Test		Longitudinal Test	
Model		32		33		34
Converged?		Yes		No		Yes
Observations		46553		46553		46553
Weighted Obs		297632.0		297632.0		297632.0
Log-likelihood		-274036.0		-273808.5		-273961.2
DOF		20		21		21
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.005	-41.0	-0.005	-40.4	-0.004	-46.6
CarTime	-0.035	-56.9	-0.036	-57.4	-0.035	-59.0
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	-0.017	-1.1	-0.025	-1.6	-0.028	-1.8
Salford	-0.241	-11.7	-0.237	-11.4	-0.218	-10.6
Wigan	-0.816	-11.5	-0.781	-10.9	-0.788	-11.2
Bolton	-0.878	-19.1	-0.855	-18.6	-0.840	-18.5
Bury	-0.834	-16.0	-0.813	-15.6	-0.757	-14.5
Rochdale	-0.553	-12.9	-0.534	-12.5	-0.453	-10.5
Oldham	-0.125	-5.0	-0.130	-5.2	-0.039	-1.5
Tameside	-0.137	-7.1	-0.148	-7.7	-0.108	-5.6
Stockport	0.074	4.9	0.069	4.6	0.084	5.7
Wilmslow	-0.172	-3.3	-0.156	-3.0	-0.173	-3.3
Glossop	-0.618	-6.1	-0.602	-5.9	-0.575	-5.7
Poynton	0.569	5.0	0.589	5.2	0.577	5.2
External	-2.355	-72.7	-2.301	-70.6	-2.337	-77.7
TP_IP	0.275	19.5	14.928	1.0	0.277	19.8
TP_IPT	4.433	56.9	98.016	1.0	4.387	57.2
TP_PM	-3.339	-82.1	-60.580	-1.0	-3.302	-83.0
TP_PMT	4.827	61.9	100.263	1.0	4.771	62.1
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	0.888	167.2	0.885	166.2	0.907	167.5
Theta_D_TP	1.000	n/a	0.042	1.0	1.000	n/a
LambdaL					-0.223	-11.5

Note that Model 33 did not converge. The results at failure indicate this is because there is little information on time period choice, so that the structural parameter tends to zero. Model 34, the longitudinal test, did not converge either.

Business

	MNL		Structural Test		Longitudinal Test	
Model		7		8		9
Converged?		Yes		No		No
Observations		5189		5189		5189
Weighted Obs		33138.2		33138.2		33138.2
Log-likelihood		-31839.7		-31821.4		-31836.9
DOF		20		21		21
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.001	-5.6	-0.001	-5.7	-0.001	-3.7
CarTime	-0.016	-8.9	-0.016	-8.8	-0.017	-7.4
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.179	3.8	0.173	3.6	0.183	3.8
Salford	-0.392	-5.6	-0.389	-5.6	-0.399	-5.7
Wigan	-0.727	-4.8	-0.698	-4.6	-0.756	-5.0
Bolton	-0.971	-7.8	-0.950	-7.6	-1.016	-8.1
Bury	-0.369	-3.3	-0.351	-3.1	-0.418	-3.7
Rochdale	-0.721	-5.9	-0.706	-5.8	-0.779	-6.3
Oldham	-0.165	-2.1	-0.158	-2.1	-0.211	-2.6
Tameside	0.284	5.2	0.285	5.2	0.259	4.6
Stockport	0.453	10.2	0.453	10.2	0.445	9.9
Wilmslow	-0.249	-1.5	-0.236	-1.4	-0.251	-1.5
Glossop	0.338	1.9	0.351	1.9	0.298	1.6
Poynton	0.464	1.3	0.481	1.4	0.456	1.3
External	-2.454	-29.5	-2.401	-28.6	-2.508	-30.3
TP_IP	0.883	19.5	16.2	2.2	0.878	19.0
TP_IPT	4.675	18.5	65.7	2.3	4.620	17.9
TP_PM	-2.222	-20.6	-27.3	-2.3	-2.196	-20.0
TP_PMT	4.354	17.2	59.3	2.3	4.310	16.9
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a
CDbefore	1.017	55.7	1.019	55.3	1.013	54.3
Theta_D_TP			0.066	2.3		
LambdaL					0.310	2.5

Note that Model 8 did not converge. The results at failure show the structural parameter tending to zero, which demonstrates there is little information on time period choice. The longitudinal test (Model 8) also failed to converge.

Education

	MNL		Structural Test		Longitudinal Test	
Model		17		18		19
Converged?		Yes		No		No
Observations		1267		1267		1267
Weighted Obs		8548.0		8548.0		8548.0
Log-likelihood		-7299.6		-7289.9		-7296.0
DOF		19		20		20
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.004	-3.4	-0.003	-2.7	-0.008	-14.0
CarTime	-0.070	-13.7	-0.074	-14.1	-0.048	-11.6
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.836	8.2	0.827	8.0	0.837	8.2
Salford	0.552	5.0	0.545	4.9	0.626	5.6
Wigan	-0.434	-0.8	-0.427	-0.8	-0.283	-0.5
Bolton	-0.324	-1.1	-0.341	-1.1	-0.021	-0.1
Bury	-0.715	-1.8	-0.714	-1.8	-0.414	-1.0
Rochdale	-0.565	-1.6	-0.574	-1.6	-0.171	-0.5
Oldham	0.201	1.5	0.165	1.2	0.375	2.6
Tameside	0.315	2.7	0.300	2.5	0.430	3.6
Stockport	0.421	4.5	0.412	4.4	0.462	5.0
Wilmslow	-0.096	-0.2	-0.081	-0.2	-0.114	-0.2
Glossop	0.000	n/a	0.000	n/a	0.000	n/a
Poynton	-0.295	-0.2	-0.288	-0.2	-0.271	-0.2
External	-1.263	-4.8	-1.314	-4.9	-0.546	-2.7
TP_IP	0.540	5.9	21.842	1.2	0.626	7.0
TP_IPT	1.983	10.3	54.570	1.2	2.080	10.9
TP_PM	-1.461	-9.4	-27.788	-1.2	-1.530	-9.9
TP_PMT	1.323	6.5	34.149	1.2	1.348	6.7
EduEmp	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	0.824	27.3	0.825	27.6	0.846	26.7
Theta_D_TP	1.000	n/a	0.044	1.2	1.000	n/a
LambdaL					-0.469	-3.6

Note that neither the structural test nor the longitudinal test converged; the results presented are those at failure. The results from the structural test suggest there is little information on time period choice.

Shopping

	MNL		Structural Test	
Model		28		29
Converged?		Yes		No
Observations		11136		11136
Weighted Obs		75039.6		75039.6
Log-likelihood		-49508.1		-49397.3
DOF		20		21
	Estimate	t-ratio	Estimate	t-ratio
Cost	0.0004	1.1	0.0009	2.7
CarTime	-0.152	-73.2	-0.158	-74.2
Manchester	0.000	n/a	0.000	n/a
Trafford	1.148	33.2	1.158	33.3
Salford	-0.053	-1.0	-0.040	-0.7
Wigan	0.045	0.1	0.103	0.3
Bolton	-0.154	-1.0	-0.129	-0.8
Bury	0.089	0.6	0.123	0.8
Rochdale	-0.676	-3.4	-0.652	-3.3
Oldham	-0.250	-3.5	-0.256	-3.6
Tameside	0.502	12.0	0.497	11.7
Stockport	0.518	15.3	0.521	15.2
Wilmslow	2.382	25.6	2.434	25.9
Glossop	1.037	2.4	1.093	2.5
Poynton	0.976	2.0	1.031	2.1
External	1.664	15.0	1.647	14.6
TP_IP	3.766	28.7	84.881	3.9
TP_IPT	5.413	17.1	120.218	3.8
TP_PM	2.029	14.9	43.415	3.8
TP_PMT	4.412	13.9	93.533	3.8
TotEmp	1.000	n/a	1.000	n/a
CDBefore	0.978	77.9	0.961	79.5
Theta_D_TP			0.051	3.9
LambdaL				

Note that the structural test did not converge. The longitudinal test was not run because of the positive cost parameter.

Other Travel

	MNL		Structural Test		Longitudinal Test	
Model		20		21		22
Converged		Yes		Yes		Yes
Observations		23916		23916		23916
Weighted Obs		159908.0		159908.0		159908.0
Log-likelihood		-131312.9		-131256.2		-131260.4
DOF		20		22		22
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.0006	-2.8	-0.0005	-2.1	-0.001	-10.7
CarTime	-0.089	-85.6	-0.091	-85.7	-0.085	-93.9
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.247	11.2	0.245	11.1	0.221	10.1
Salford	-0.369	-11.6	-0.368	-11.5	-0.345	-10.9
Wigan	-0.313	-2.9	-0.299	-2.8	-0.263	-2.5
Bolton	-0.835	-11.0	-0.832	-10.9	-0.726	-9.6
Bury	-0.471	-6.5	-0.465	-6.4	-0.251	-3.4
Rochdale	-0.562	-7.7	-0.559	-7.7	-0.281	-3.8
Oldham	-0.053	-1.6	-0.068	-2.0	0.125	3.5
Tameside	0.071	2.6	0.066	2.4	0.117	4.2
Stockport	0.089	4.3	0.090	4.3	0.094	4.6
Wilmslow	-0.231	-2.5	-0.222	-2.3	-0.252	-2.7
Glossop	0.239	1.7	0.252	1.8	0.406	2.9
Poynton	0.044	0.2	0.053	0.3	0.028	0.1
External	-1.500	-29.9	-1.495	-29.6	-1.434	-35.2
TP_IP	2.183	58.9	18.664	2.0	2.195	59.7
TP_IPT	2.859	41.9	23.866	2.0	2.886	42.6
TP_PM	0.452	10.6	5.382	1.9	0.429	10.2
TP_PMT	1.945	27.6	15.541	2.0	1.937	27.7
L_S_M	1.000	n/a	1.000	n/a	1.000	n/a
ServEmp	2.566	2.5	2.547	2.5	2.659	2.6
CDBefore	0.911	135.6	0.905	137.2	0.922	139.4
Theta_D_TP			0.141	2.1		
LambdaL					-0.362	-17.2

Non-Home-Based Business

	MNL		Structural Test		Longitudinal Test	
Model		8		9		10
Converged		Yes		Yes		No
Observations		8719		8719		8719
Weighted Obs		66248.5		66248.5		66248.5
Log-likelihood		-52721.1		-52712.9		-52718.4
DOF		18		19		19
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.006	-19.6	-0.006	-19.0	-0.006	-25.6
CarTime	-0.032	-9.8	-0.034	-10.3	-0.030	-12.2
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.177	4.1	0.178	4.1	0.179	4.2
Salford	-0.112	-2.6	-0.110	-2.5	-0.107	-2.5
Wigan	-0.292	-2.6	-0.282	-2.5	-0.282	-2.6
Bolton	-0.314	-4.0	-0.315	-4.0	-0.302	-4.0
Bury	-0.112	-1.4	-0.106	-1.3	-0.105	-1.4
Rochdale	-0.111	-1.4	-0.103	-1.3	-0.116	-1.5
Oldham	0.292	5.9	0.298	6.0	0.277	5.7
Tameside	0.281	4.9	0.286	5.0	0.273	4.8
Stockport	0.663	17.9	0.664	17.9	0.662	18.2
Wilmslow	-0.112	-0.8	-0.107	-0.8	-0.100	-0.7
Glossop	1.077	4.9	1.102	5.0	1.028	4.7
Poynton	-0.114	-0.2	-0.104	-0.2	-0.107	-0.2
External	-1.431	-18.5	-1.427	-18.5	-1.386	-18.9
TP_IP	3.256	47.1	14.413	1.3	3.176	44.2
TP_PM	0.842	11.1	4.031	1.3	0.819	11.1
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	0.864	80.9	0.865	80.8	0.915	40.8
Theta_D_TP	1.000	n/a	0.240	1.4	1.000	n/a
LambdaL					0.150	2.5

Note that the longitudinal test did not converge.

Non-Home-Based Other

	MNL		Structural Test		Longitudinal Test	
Model		8		9		10
Converged?		Yes		No		No
Observations		18934		18934		18934
Weighted Obs		149741.0		149741.0		149741.0
Log-likelihood		-110273.7		-110145.3		-110121.1
DOF		19		20		20
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.012	-25.3	-0.012	-23.9	-0.012	-44.6
CarTime	-0.110	-51.4	-0.117	-53.4	-0.106	-66.9
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.404	15.2	0.487	18.3	0.405	15.5
Salford	-0.268	-9.2	-0.241	-8.2	-0.223	-7.8
Wigan	-0.267	-2.9	-0.163	-1.8	-0.211	-2.3
Bolton	-0.770	-10.9	-0.696	-9.9	-0.689	-9.9
Bury	-0.223	-3.5	-0.146	-2.3	-0.122	-1.9
Rochdale	-0.091	-1.5	-0.006	-0.1	0.083	1.3
Oldham	0.353	10.4	0.400	11.7	0.515	14.6
Tameside	0.412	11.1	0.472	12.9	0.524	14.0
Stockport	0.531	22.5	0.591	24.9	0.513	21.9
Wilmslow	0.194	2.1	0.290	3.2	0.156	1.7
Glossop	1.242	7.2	1.401	8.3	1.920	10.9
Poynton	-0.116	-0.4	-0.018	-0.1	-0.115	-0.4
External	-0.986	-17.8	-0.891	-16.0	-0.980	-20.8
TP_IP	2.321	64.0	688.152	3.0	2.317	65.3
TP_PM	1.078	27.9	322.917	3.0	1.044	27.4
SizeMult	1.000	n/a	1.000	n/a	1.000	n/a
ServEmp	2.170	48.5	1.989	50.0	2.161	50.0
CDBefore	0.883	117.6	0.874	120.3	0.909	118.2
Theta_D_TP	1.000	n/a	0.004	3.0	1.000	n/a
LambdaL					-0.466	-16.3

Note that neither the structural test not the longitudinal test converged.

Public Transport Interview Models

Not all of the models presented in this section have converged, the second row in each table of model results clarifies whether the model in question has converged.

Model Exclusions

	Commute		Home-Business		Home-Education	
Total observations	29,619	100.0%	2,087	100.0%	6,899	100.0%
No attraction variable in dest zone					1,761	25.5%
PT chosen, no path in LOS	46	0.2%	3	0.1%	4	0.1%
Imputed records	740	2.5%	113	5.4%	155	2.2%
Off-peak records	1,305	4.4%	44	2.1%	316	4.6%
Screenline crossing prob = zero	799	2.7%	78	3.7%	383	5.6%
Sline crossing prob >0 and < 0.5	1,723	5.8%	78	3.7%	515	7.5%
Estimation sample	25,006	84.4%	1,771	84.9%	3,765	54.6%

	Shopping		Other Travel	
Total observations	8,094	100.0%	11,346	100.0%
No attraction variable in dest zone	25	0.3%	11	0.1%
PT chosen, no path in LOS	243	3.0%	548	4.8%
Imputed records	344	4.3%	535	4.7%
Off-peak records	312	3.9%	462	4.1%
Screenline crossing prob = zero	448	5.5%	724	6.4%
Sline crossing prob >0 and < 0.5	6,722	83.0%	9,066	79.9%
Estimation sample	8,094	100.0%	11,346	100.0%

	NHB Business		NHB Other	
Total observations	754	100.0%	6,063	100.0%
PT chosen, no path in LOS	19	2.5%	246	4.1%
Imputed records	63	8.4%	328	5.4%
Off-peak records	4	0.5%	300	4.9%
Screenline crossing prob = zero	32	4.2%	674	11.1%
Sline crossing prob >0 and < 0.5	49	6.5%	24	0.4%
Estimation sample	587	77.9%	4,491	74.1%

Commute

	MNL		Structural Test		Longitudinal Test	
Model		33		34		35
Converged		Yes		Yes		No
Observations		25006		25006		24994
Weighted Obs		25006		25006		24994
Log-likelihood		-116323.2		-116312.1		-116177.6
DOF		20		21		21
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.004	-30.1	-0.004	-30.5	-0.005	-84.3
PTIVtime	-0.021	-55.8	-0.021	-55.5	-0.020	-56.6
PTwktime	-0.016	-42.7	-0.016	-42.6	-0.014	-40.2
PTWttime	-0.028	-34.3	-0.028	-34.2	-0.027	-34.1
Transfers	-0.017	-1.0	-0.009	-0.5	0.022	1.7
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	-0.393	-14.9	-0.391	-14.8	-0.367	-14.0
Salford	-0.447	-14.8	-0.445	-14.7	-0.435	-14.5
Wigan	-1.612	-7.0	-1.599	-7.0	-1.545	-6.8
Bolton	-1.817	-13.3	-1.807	-13.3	-1.718	-12.7
Bury	-1.247	-12.2	-1.237	-12.1	-1.120	-11.1
Rochdale	-1.558	-14.2	-1.556	-14.2	-1.522	-14.0
Oldham	-1.331	-22.2	-1.331	-22.2	-1.262	-21.2
Tameside	-0.796	-17.4	-0.796	-17.4	-0.762	-16.8
Stockport	-0.513	-16.3	-0.512	-16.3	-0.484	-15.5
Wilmslow	-0.793	-6.1	-0.784	-6.0	-0.706	-5.5
Glossop	-0.610	-2.5	-0.602	-2.5	-0.507	-2.1
Poynton	-0.046	-0.2	-0.037	-0.1	0.003	0.0
External	-1.660	-25.7	-1.643	-25.4	-1.524	-24.1
TP_IP	0.474	31.2	1.017	4.3	0.468	31.0
TP_IPT	3.766	26.6	7.999	4.3	3.722	26.5
TP_PM	-2.461	-57.7	-5.203	-4.3	-2.439	-57.6
TP_PMT	3.951	27.9	8.362	4.3	3.919	27.9
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a
PTBefore	0.970	113.8	0.969	113.8	0.987	112.1
Theta_D_TP			0.474	4.4		
LambdaL					-1.095	-13.2

Note that the longitudinal test did not converge.

Business

	MNL		Structural Test	
Model		1		2
Converged?		Yes		Yes
Observations		1771		1771
Weighted Obs		5575.3		5575.3
Log-likelihood		-8798.3		-8798.3
DOF		23		24
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.005	-14.0	-0.005	-13.9
PTIVtime	0.001	0.7	0.001	0.9
PTwktime	-0.005	-11.4	-0.005	-11.3
PTWttime	-0.021	-8.0	-0.022	-8.2
Transfers	-0.149	-2.9	-0.151	-2.9
Manchester	0.000	n/a	0.000	n/a
Trafford	-1.064	-8.3	-1.064	-8.3
Salford	-0.704	-5.8	-0.702	-5.8
Wigan	-1.906	-4.2	-1.902	-4.2
Bolton	-2.125	-5.7	-2.123	-5.7
Bury	-1.646	-4.3	-1.645	-4.3
Rochdale	-2.511	-5.1	-2.514	-5.1
Oldham	-2.142	-6.8	-2.142	-6.8
Tameside	-1.330	-7.1	-1.330	-7.1
Stockport	-1.224	-8.3	-1.223	-8.3
Wilmslow	-1.186	-2.2	-1.172	-2.2
Glossop	-1.220	-1.5	-1.202	-1.5
Poynton	-0.572	-0.5	-0.555	-0.5
External	-1.909	-12.5	-1.911	-12.5
TP_IP	0.851	13.1	3.176	1.1
TP_IPT	4.920	7.4	18.421	1.1
TP_PM	-2.096	-12.9	-7.857	-1.1
TP_PMT	4.703	7.1	17.609	1.1
TotEmp	1.000	n/a	1.000	n/a
PTBefore	0.947	42.8	0.947	42.8
Theta_D_TP			0.268	1.1

The longitudinal test was not run because the in-vehicle time parameter is wrong-signed, and so time savings have the counter-intuitive effect of worsening utility.

Education

	MNL		Structural Test		Longitudinal Test	
Model		3		4		5
Converged?		Yes		Yes		No
Observations		3765		3765		3761
Weighted Obs		11643.6		11643.6		11627.4
Log-likelihood		-18350.0		-18350.0		-18356.1
DOF		22		23		23
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.001	-2.5	-0.001	-2.5	-0.001	-6.9
PTIVtime	-0.027	-33.6	-0.027	-33.5	-0.026	-32.8
PTwktime	-0.020	-23.6	-0.020	-23.6	-0.020	-23.7
PTWttime	-0.032	-20.6	-0.032	-20.7	-0.032	-20.3
Transfers	-0.481	-9.1	-0.478	-9.0	-0.486	-15.3
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.875	16.0	0.874	16.0	0.874	16.1
Salford	0.887	13.3	0.892	13.3	0.879	13.2
Wigan	-0.589	-0.9	-0.583	-0.9	-0.599	-0.9
Bolton	-0.210	-0.7	-0.200	-0.7	-0.229	-0.8
Bury	-0.818	-2.6	-0.808	-2.6	-0.828	-2.7
Rochdale	-1.055	-3.2	-1.056	-3.2	-1.061	-3.2
Oldham	-0.115	-1.1	-0.121	-1.1	-0.102	-1.0
Tameside	1.142	18.8	1.138	18.7	1.158	19.0
Stockport	0.670	11.8	0.670	11.8	0.676	11.9
Wilmslow	-0.126	-0.4	-0.116	-0.4	-0.121	-0.4
Glossop	-1.208	-1.1	-1.206	-1.1	-1.214	-1.1
Poynton	0.000	n/a	0.000	n/a	0.000	n/a
External	-0.457	-3.6	-0.453	-3.6	-0.473	-4.2
TP_IP	0.507	10.4	1.839	0.8	0.508	10.4
TP_IPT	6.154	8.8	21.763	0.8	6.154	8.8
TP_PM	-2.720	-16.5	-9.633	-0.8	-2.723	-16.5
TP_PMT	5.899	8.4	20.828	0.8	5.906	8.4
EduEmp	1.000	n/a	1.000	n/a	1.000	n/a
PTBefore	1.071	52.1	1.071	52.0	1.069	52.5
Theta_D_TP			0.283	0.8		
LambdaL					0.221	0.9

Note that the longitudinal test did not converge; the values at the point of failure are reported.

Shopping

	MNL		Structural Test		Longitudinal Test	
Model		10		10		10
Converged?		Yes		No		No
Observations		6722		6722		6722
Weighted Obs		22044.1		22044.1		22044.1
Log-likelihood		-23802.2		-23802.2		-23790.4
DOF		21		21		21
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.003	-10.5	-0.003	0.0	-0.003	-15.7
PTIVtime	-0.024	-33.0	-0.024	0.0	-0.024	-33.3
PTwktime	-0.037	-60.2	-0.037	0.0	-0.037	-40.9
PTWttime	-0.047	-30.7	-0.047	0.0	-0.047	-27.1
Transfers	-0.639	-20.1	-0.639	0.0	-0.654	-19.9
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.078	0.2	0.078	0.0	0.089	1.9
Salford	-0.979	-2.3	-0.980	0.0	-0.951	-9.5
Wigan	-1.958	-1.4	-1.958	-0.6	-1.792	-1.7
Bolton	0.908	2.0	0.908	0.0	0.942	6.9
Bury	0.568	1.3	0.568	0.0	0.613	5.0
Rochdale	-1.021	-1.5	-1.021	-0.1	-1.000	-3.6
Oldham	-0.578	-1.3	-0.578	0.0	-0.557	-4.7
Tameside	0.444	0.9	0.443	0.0	0.454	6.7
Stockport	-0.180	-0.4	-0.180	0.0	-0.166	-2.7
Wilmslow	-1.458	-1.5	-1.458	-0.2	-1.427	-2.6
Glossop	1.070	1.3	1.069	0.1	1.112	3.0
Poynton	3.322	4.5	3.323	0.2	3.359	13.2
External	-1.220	-7.1	-1.220	-0.4	-1.184	-6.8
TP_IP	3.918	75.3	3.583	0.3	3.998	34.3
TP_IPT	166.089	2954.0	166.105	14.9	163.704	0.0
TP_PM	1.405	4.5	1.286	0.2	1.438	11.7
TP_PMT	164.707	517.9	164.843	2.5	162.283	0.0
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a
PTBefore	0.971	77.7	0.971	0.0	0.971	61.5
Theta_D_TP			1.085	0.0		
LambdaL					-0.538	-4.0

Note that neither the structural nor the longitudinal test converged.

Other Travel

	MNL		Structural Test		Longitudinal Test	
Model		12		13		14
Converged?		Yes		No		Yes
Observations		9066		9066		9066
Weighted Obs		28753.5		28753.5		28753.5
Log-likelihood		-45080.1		-45072.5		-45081.2
DOF		24		24		24
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.004	-18.0	-0.004	-18.3	-0.004	-22.6
PTIVtime	-0.008	-16.7	-0.008	-16.8	-0.008	-16.5
PTwktime	-0.009	-28.3	-0.009	-28.2	-0.008	-28.0
PTWttime	-0.007	-6.7	-0.007	-6.5	-0.007	-6.6
Transfers	-0.328	-12.1	-0.322	-11.9	-0.320	-13.0
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	-0.718	-14.5	-0.720	-14.6	-0.716	-14.5
Salford	-0.696	-12.8	-0.697	-12.8	-0.695	-12.8
Wigan	-1.711	-7.9	-1.709	-7.9	-1.703	-7.9
Bolton	-1.788	-11.6	-1.786	-11.6	-1.778	-11.5
Bury	-0.593	-5.8	-0.588	-5.8	-0.585	-5.8
Rochdale	-1.158	-9.1	-1.156	-9.1	-1.156	-9.1
Oldham	-1.223	-12.1	-1.222	-12.1	-1.219	-12.1
Tameside	-0.554	-8.3	-0.552	-8.2	-0.554	-8.3
Stockport	-0.731	-12.8	-0.729	-12.8	-0.728	-12.8
Wilmslow	-1.863	-6.4	-1.862	-6.4	-1.855	-6.4
Glossop	-0.707	-2.6	-0.707	-2.6	-0.697	-2.6
Poynton	-1.000	-2.0	-0.993	-2.0	-0.995	-2.0
External	-1.908	-24.2	-1.894	-24.0	-1.891	-24.1
TP_IP	2.969	47.8	492.092	0.8	2.963	47.6
TP_IPT	4.141	21.3	687.513	0.8	4.133	21.2
TP_PM	1.063	15.4	176.127	0.8	1.061	15.4
TP_PMT	3.057	15.5	507.573	0.8	3.051	15.5
SizeMult	1.000	n/a	1.000	n/a	1.000	n/a
ServEmp	16.142	12.4	2.784	28.6	2.776	28.6
PTBefore	0.925	96.0	0.923	95.9	0.928	92.2
Theta_D_TP			0.006	0.8		
LambdaL					-0.135	-1.1

Note that the structural test did not converge.

Non-Home-Based Business

	MNL		Structural Test		Structural Test	
Model		1		2		3
Converged?		Yes		Yes		Yes
Observations		587		587		587
Weighted Obs		2342.9		2342.9		2342.9
Log-likelihood		-3099.9		-3097.3		-2967.5
DOF		20		21		21
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.001	-1.0	-0.001	-0.6	0.000	-3.0
PTIVtime	0.018	7.4	0.017	7.1	0.000	1.8
PTwktime	-0.005	-4.3	-0.005	-4.5	0.000	-3.8
PTWttime	-0.020	-2.7	-0.020	-2.8	0.000	-1.2
Transfers	-0.746	-4.7	-0.776	-4.9	-0.023	-3.5
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	-1.755	-7.2	-1.750	-7.2	-0.042	-4.0
Salford	-1.516	-7.3	-1.498	-7.3	-0.042	-4.4
Wigan	-3.650	-5.2	-3.626	-5.2	-0.091	-3.3
Bolton	-2.269	-6.4	-2.254	-6.4	-0.057	-3.8
Bury	-2.127	-5.5	-2.121	-5.5	-0.054	-3.5
Rochdale	-2.888	-6.0	-2.882	-6.0	-0.073	-3.7
Oldham	-2.351	-6.8	-2.344	-6.8	-0.062	-4.1
Tameside	-2.686	-6.3	-2.696	-6.3	-0.062	-3.6
Stockport	-2.124	-8.2	-2.117	-8.2	-0.042	-3.8
Wilmslow	-1.407	-2.6	-1.405	-2.6	-0.025	-1.4
Glossop	0.000	n/a	0.000	n/a	0.000	n/a
Poynton	-1.295	-1.2	-1.304	-1.2	-0.020	-0.6
External	-6.015	-32.9	-5.983	-33.4	-0.145	-5.5
TP_IP	1.701	12.7	0.546	2.5	1.935	14.3
TP_PM	-0.549	-2.9	-0.350	-4.0	-0.329	-1.7
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a
PTBefore	1.110	23.4	1.113	23.1	1.074	24.3
Theta_D_TP			2.510	3.5		
Theta_TP_D					32.073	6.2

Due to the wrong-signed PT in-vehicle time parameter the longitudinal test was not run.

Non-Home-Based Other Travel

	MNL		Structural Test		Structural Test	
Model		1		2		2
Converged?		Yes		No		No
Observations		4419		4419		4419
Weighted Obs		16686.0		16686.0		16686.0
Log-likelihood		-20977.9		-20966.5		-20977.6
DOF		21		22		22
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.005	-8.7	-0.006	-8.9	-0.006	-11.0
PTIVtime	-0.022	-15.8	-0.022	-15.9	-0.022	-15.2
PTwktime	-0.039	-24.4	-0.039	-24.3	-0.039	-24.3
PTWttime	-0.036	-11.2	-0.037	-11.4	-0.036	-11.3
Transfers	-0.884	-11.6	-0.860	-11.2	-0.858	-12.3
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.056	0.9	0.054	0.8	0.058	0.9
Salford	-0.712	-9.4	-0.707	-9.3	-0.710	-9.3
Wigan	-2.123	-4.3	-2.091	-4.2	-2.112	-4.3
Bolton	-1.131	-5.8	-1.113	-5.7	-1.119	-5.8
Bury	-0.628	-4.2	-0.612	-4.1	-0.618	-4.1
Rochdale	-1.513	-6.7	-1.504	-6.7	-1.513	-6.7
Oldham	-0.565	-5.5	-0.561	-5.4	-0.563	-5.4
Tameside	-0.132	-1.1	-0.118	-1.0	-0.131	-1.1
Stockport	-0.451	-4.7	-0.449	-4.7	-0.452	-4.7
Wilmslow	-2.053	-3.4	-2.034	-3.4	-2.045	-3.4
Glossop	-1.671	-1.6	-1.653	-1.6	-1.649	-1.6
Poynton	0.000	n/a	0.000	n/a	0.000	n/a
External	-1.140	-9.4	-1.094	-9.0	-1.109	-9.1
TP_IP	3.008	35.4	682.695	0.5	3.007	35.4
TP_PM	1.855	21.2	418.214	0.5	1.855	21.2
SizeMult	1.000	n/a	1.000	n/a	1.000	n/a
ServEmp	3.405	15.0	3.403	15.0	3.402	15.0
PTBefore	1.008	55.8	1.008	55.7	1.008	56.0
Theta_D_TP			0.004	0.5		
LambdaL					-0.115	-0.6

Note that neither the structural nor the longitudinal test converged.

Pooled Intercept Models

All of the models presented in this section have converged.

Commute

	MNL		Longitudinal Test	
Model		24		25
Observations		46553		46553
Weighted Obs		297632.0		297632.0
Log-likelihood		-288051.3		-287999.9
DOF		22		23
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.005	-46.3	-0.005	-55.3
CarTime	-0.036	-57.6	-0.035	-58.5
PTIVtime	-0.024	-21.3	-0.024	-22.1
PTwttime	-0.033	-19.1	-0.033	-19.5
PTwktime	-0.018	-19.2	-0.018	-19.6
Transfers	-0.107	-4.4	-0.113	-4.7
Manchester	0.000	n/a	0.000	n/a
Trafford	-0.099	-6.8	-0.109	-7.5
Salford	-0.298	-15.6	-0.284	-14.9
Wigan	-0.850	-12.1	-0.833	-11.9
Bolton	-0.945	-20.9	-0.915	-20.3
Bury	-0.895	-17.9	-0.839	-16.7
Rochdale	-0.654	-15.6	-0.583	-13.8
Oldham	-0.283	-11.6	-0.220	-8.8
Tameside	-0.230	-12.4	-0.209	-11.2
Stockport	-0.011	-0.8	-0.003	-0.2
Wilmslow	-0.233	-4.5	-0.238	-4.7
Glossop	-0.636	-6.4	-0.608	-6.2
Poynton	0.529	4.8	0.532	4.8
External	-2.263	-72.3	-2.241	-75.5
TotEmp	1.000	n/a	1.000	n/a
CDBefore	0.876	158.9	0.885	158.3
PTBefore	0.836	32.3	0.837	33.5
PTAfter	0.861	31.6	0.860	32.9
LambdaL			-0.180	-9.7

Business

	MNL		Longitudinal Test	
Model		9		10
Observations		6960		6960
Weighted Obs		38713.5		38713.5
Log-likelihood		-36536.5		-36526.4
DOF		22		23
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.002	-5.6	-0.002	-9.1
CarTime	-0.020	-16.5	-0.014	-7.2
PTIVtime	-0.006	-2.5	-0.005	-2.4
PTwttime	-0.040	-5.5	-0.038	-5.5
PTwktime	-0.009	-6.1	-0.008	-6.1
Transfers	-1.256	-8.8	-1.209	-9.0
Manchester	0.000	n/a	0.000	n/a
Trafford	0.113	2.2	0.123	2.5
Salford	-0.457	-6.3	-0.430	-6.2
Wigan	-0.855	-5.5	-0.787	-5.1
Bolton	-1.182	-9.0	-1.063	-8.2
Bury	-0.480	-4.1	-0.405	-3.5
Rochdale	-0.910	-7.1	-0.809	-6.4
Oldham	-0.267	-3.3	-0.208	-2.6
Tameside	0.243	4.3	0.281	5.0
Stockport	0.450	9.4	0.467	10.0
Wilmslow	-0.367	-2.1	-0.343	-2.0
Glossop	0.330	1.8	0.365	2.0
Poynton	0.677	1.9	0.637	1.9
External	-2.879	-37.1	-2.669	-30.6
TotEmp	1.000	n/a	1.000	n/a
CDBefore	0.705	15.5	0.783	21.0
PTBefore	0.584	11.2	0.618	11.2
PTAfter	0.584	11.3	0.617	11.3
LambdaL			-0.295	-4.0

Education

	MNL		Longitudinal Test	
Model		9		10
Observations		5032		5032
Weighted Obs		20191.5		20191.5
Log-likelihood		-22621.3		-22613.4
DOF		22		23
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.002	-3.7	-0.002	-13.9
CarTime	-0.087	-29.7	-0.083	-41.9
PTIVtime	-0.023	-11.6	-0.023	-12.9
PTwttime	-0.028	-10.5	-0.029	-11.3
PTwktime	-0.017	-10.5	-0.017	-11.2
Transfers	-0.387	-6.7	-0.427	-10.0
Manchester	0.000	n/a	0.000	n/a
Trafford	0.801	12.6	0.810	13.6
Salford	0.709	11.5	0.729	12.0
Wigan	-0.388	-1.1	-0.389	-1.1
Bolton	-0.265	-1.4	-0.241	-1.3
Bury	-0.678	-3.0	-0.626	-2.7
Rochdale	-0.723	-3.4	-0.651	-3.1
Oldham	0.023	0.3	0.075	0.9
Tameside	0.762	13.2	0.795	13.6
Stockport	0.521	10.2	0.532	10.6
Wilmslow	-0.100	-0.4	-0.112	-0.5
Glossop	-1.980	-1.7	-2.006	-1.7
Poynton	-0.834	-0.9	-0.847	-0.9
External	-0.854	-6.8	-0.939	-8.8
EduEmp	1.000	n/a	1.000	n/a
CDBefore	0.802	35.1	0.820	35.7
PTBefore	1.181	12.7	1.147	14.5
PTAfter	1.086	12.9	1.056	14.8
LambdaL			0.774	13.6

Shopping

	MNL		Structural Test		Longitudinal Test	
Model		28		29		30
Observations		17858		17858		17858
Weighted Obs		97083.7		97083.7		97083.7
Log-likelihood		-73214.6		-73154.9		-72988.8
DOF		26		27		27
	Estimate	t-ratio	Estimate	t-ratio	Estimate	r-ratio
Cost	-0.003	-13.0	-0.003	-9.8	-0.003	-18.1
CarTime	-0.136	-84.0	-0.141	-82.2	-0.133	-92.3
PTIVtime	-0.018	-14.8	-0.020	-14.9	-0.016	-13.9
PTwttime	-0.043	-16.6	-0.045	-16.3	-0.040	-15.4
PTwktime	-0.030	-17.0	-0.032	-16.9	-0.028	-15.8
Transfers	-0.430	-9.1	-0.535	-10.2	-0.391	-10.0
Manchester	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.355	13.0	0.370	13.3	0.329	12.3
Salford	-0.066	-1.5	-0.041	-0.9	-0.047	-1.1
Wigan	-0.170	-0.6	-0.127	-0.4	-0.142	-0.5
Bolton	0.212	2.1	0.208	2.0	0.321	3.3
Bury	0.465	5.0	0.439	4.5	0.694	7.7
Rochdale	-0.843	-5.6	-0.842	-5.5	-0.387	-2.7
Oldham	-0.538	-9.7	-0.549	-9.7	-0.278	-4.8
Tameside	0.392	11.6	0.395	11.5	0.438	12.9
Stockport	0.345	12.3	0.357	12.5	0.328	11.7
Wilmslow	1.400	16.4	1.459	16.9	1.312	15.5
Glossop	0.561	2.0	0.579	2.0	0.838	3.2
Poynton	1.742	7.5	1.792	7.4	1.690	7.7
External	0.175	2.1	0.164	1.9	0.096	1.3
TP_IP	4.160	37.7	22.074	3.1	4.015	39.6
TP_IPT	5.758	20.0	30.324	3.1	5.660	20.1
TP_PM	2.381	21.6	12.172	3.1	2.183	21.6
TP_PMT	4.704	16.3	23.970	3.1	4.565	16.2
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	0.931	87.7	0.921	88.8	0.960	89.8
PTBefore	1.252	19.5	1.170	19.2	1.364	18.0
PTAfter	1.283	19.4	1.197	19.1	1.425	17.7
Theta_D_TP			0.209	3.2		
LambdaL					-0.433	-17.6

Other Travel

	MNL		Longitudinal Test	
Model		24		25
Observations		46553		46553
Weighted Obs		297632.0		297632.0
Log-likelihood		-288051.3		-287999.9
DOF		22		23
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.005	-46.3	-0.005	-55.3
CarTime	-0.036	-57.6	-0.035	-58.5
PTIVtime	-0.024	-21.3	-0.024	-22.1
PTwttime	-0.033	-19.1	-0.033	-19.5
PTwktime	-0.018	-19.2	-0.018	-19.6
Transfers	-0.107	-4.4	-0.113	-4.7
Manchester	0.000	n/a	0.000	n/a
Trafford	-0.099	-6.8	-0.109	-7.5
Salford	-0.298	-15.6	-0.284	-14.9
Wigan	-0.850	-12.1	-0.833	-11.9
Bolton	-0.945	-20.9	-0.915	-20.3
Bury	-0.895	-17.9	-0.839	-16.7
Rochdale	-0.654	-15.6	-0.583	-13.8
Oldham	-0.283	-11.6	-0.220	-8.8
Tameside	-0.230	-12.4	-0.209	-11.2
Stockport	-0.011	-0.8	-0.003	-0.2
Wilmslow	-0.233	-4.5	-0.238	-4.7
Glossop	-0.636	-6.4	-0.608	-6.2
Poynton	0.529	4.8	0.532	4.8
External	-2.263	-72.3	-2.241	-75.5
TotEmp	1.000	n/a	1.000	n/a
CDBefore	0.876	158.9	0.885	158.3
PTBefore	0.836	32.3	0.837	33.5
PTAfter	0.861	31.6	0.860	32.9
LambdaL			-0.180	-9.7

Non-Home-Based Business

	MNL		Longitudinal Test	
Model		7		8
Observations		9303		9303
Weighted Obs		68578.67		68578.67
Log-likelihood		-51856.1		-51837.2
DOF		22		23
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.005	-20.4	-0.005	-27.0
CarTime	-0.041	-14.0	-0.036	-12.8
PTIVtime	-0.030	-2.6	-0.029	-2.6
PTwttime	-0.063	-2.7	-0.064	-2.7
PTwktime	-0.037	-3.0	-0.036	-3.0
Transfers	-1.711	-3.6	-1.650	-3.6
Manchester	0.000	n/a	0.000	n/a
Trafford	0.072	1.7	0.074	1.7
Salford	-0.191	-4.5	-0.173	-4.1
Wigan	-0.439	-4.0	-0.408	-3.7
Bolton	-0.461	-6.0	-0.401	-5.3
Bury	-0.233	-3.0	-0.188	-2.4
Rochdale	-0.233	-3.1	-0.166	-2.2
Oldham	0.201	4.1	0.250	5.0
Tameside	0.186	3.2	0.219	3.8
Stockport	0.566	15.3	0.556	15.2
Wilmslow	-0.196	-1.4	-0.219	-1.6
Glossop	0.983	4.5	1.164	5.3
Poynton	-0.151	-0.3	-0.146	-0.3
External	-1.627	-23.1	-1.561	-23.0
TotEmp	1.000	n/a	1.000	n/a
CDBefore	0.857	73.9	0.879	69.8
PTBefore	0.691	4.5	0.705	4.6
PTAfter	0.680	4.5	0.691	4.7
LambdaL			-0.340	-5.8

Non-Home-Based Other

	MNL		Longitudinal Test	
Model		8		9
Observations		23425		23425
Weighted Obs		166427.0		166427.0
Log-likelihood		-118363.6		-118183.5
DOF		24		25
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.004	-17.0	-0.004	-25.2
CarTime	-0.137	-79.1	-0.128	-87.9
PTIVtime	-0.055	-6.1	-0.064	-5.8
PTwttime	-0.098	-6.0	-0.116	-5.4
PTwktime	-0.088	-6.8	-0.104	-6.8
Transfers	-2.909	-7.3	-3.359	-6.5
Manchester	0.000	n/a	0.000	n/a
Trafford	0.299	11.7	0.278	10.9
Salford	-0.255	-9.2	-0.226	-8.1
Wigan	-0.401	-4.5	-0.356	-4.0
Bolton	-0.933	-14.1	-0.850	-12.9
Bury	-0.338	-5.6	-0.240	-4.0
Rochdale	-0.275	-4.6	-0.094	-1.6
Oldham	0.277	8.5	0.458	13.6
Tameside	0.401	11.4	0.512	14.4
Stockport	0.485	21.2	0.454	19.9
Wilmslow	0.139	1.6	0.084	1.0
Glossop	1.374	8.3	2.059	12.4
Poynton	-0.108	-0.3	-0.123	-0.4
External	-1.487	-31.8	-1.441	-33.0
SizeMult	1.000	n/a	1.000	n/a
ServEmp	1.984	52.0	2.035	52.1
CDBefore	0.880	115.4	0.905	145.7
PTBefore	0.524	8.1	0.455	7.3
PTAfter	0.508	8.1	0.441	7.2
LambdaL			-0.444	-19.3

Appendix F: Household Interview Models

All of the models presented in this Appendix have converged.

Model Exclusions

	Commute		Business		Education	
Total observations	3,827	100.0%	302	100.0%	4,440	100.0%
Mode not modelled	35	0.9%	5	1.7%	33	0.7%
No attraction variable in dest zone					178	4.0%
Car driver chosen, no licence	9	0.2%	2	0.7%	2	0.0%
Car driver chosen, no cars in HH	8	0.2%	2	0.7%	2	0.0%
PT chosen, no path in LOS	50	1.3%	5	1.7%	153	3.4%
Estimation sample	3,725	97.3%	288	95.4%	4,072	91.7%
Total observations	3,827	100.0%	302	100.0%	4,440	100.0%

	Shopping		Other Travel	
Total observations	2597	100.0%	5153	100.0%
Mode not modelled	73	2.8%	175	3.4%
Car driver chosen, no licence	3	0.1%	15	0.3%
Car driver chosen, no cars in HH	6	0.2%	9	0.2%
PT chosen, no path in LOS	72	2.8%	138	2.7%
Chosen TP comb. excluded	2	0.1%	0	0.0%
Estimation sample	2,441	94.0%	4,816	93.5%

Commute

	MNL		Structural Test	
Model		53		53T2
Observations		3725		3725
Log-likelihood		-20027.1		-20011.4
DOF		40		41
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.003	-7.6	-0.003	-7.4
LogCost	-0.532	-10.9	-0.534	-10.6
CarTime	-0.040	-16.1	-0.040	-15.7
CarPDist	-0.045	-9.7	-0.045	-9.6
PTIVtime	-0.022	-12.5	-0.022	-11.9
PTwttime	-0.020	-5.6	-0.023	-5.9
PTwktime	-0.017	-7.8	-0.017	-7.4
WalkDist	-0.489	-20.3	-0.513	-19.8
CycleDist	-0.230	-11.3	-0.236	-11.0
1CrCmpCrD	-2.067	-18.2	-4.727	-4.4
2PlCmpCrD	-1.447	-8.9	-3.287	-4.0
PssOpt2HH	1.186	6.4	2.667	3.7
PssOpt3HH	1.055	6.8	2.383	3.8
SEGAB_PT	0.937	5.2	2.164	3.4
SEGC1_PT	0.735	6.1	1.731	3.6
SEGDE_Walk	0.562	4.6	1.164	3.2
PTwkWalk	1.158	8.9	2.529	4.1
MaleCycle	1.345	5.1	3.041	3.4
HmMancPT	0.514	3.8	1.444	3.0
CarP	-5.103	-25.4	-10.817	-4.7
PT	-1.551	-8.6	-6.564	-3.3
Walk	-3.208	-13.2	-8.223	-4.0
Cycle	-6.417	-18.0	-14.087	-4.5
Intrazonal	-0.207	-1.7	-0.228	-1.9
CarPIZ	-0.113	-0.5	-0.113	-0.5
WalkIZ	0.894	5.0	0.854	4.6
CycleIZ	0.442	1.2	0.378	1.0
Manchester	0.000	n/a	0.000	n/a
Trafford	-0.045	-0.6	-0.053	-0.7
Salford	-0.098	-1.3	-0.115	-1.5
Wigan	-0.444	-4.3	-0.446	-4.2
Bolton	-0.436	-4.8	-0.410	-4.5
Bury	-0.413	-4.0	-0.445	-4.2
Rochdale	-0.229	-2.4	-0.246	-2.5
Oldham	-0.225	-2.6	-0.231	-2.6
Tameside	-0.226	-2.7	-0.242	-2.9
Stockport	-0.209	-2.9	-0.197	-2.7
Wilmslow	0.076	0.4	0.074	0.4
Glossop	-0.615	-2.7	-0.453	-1.9
Poynton	0.817	3.0	0.813	2.8

	MNL		Structural Test	
External	-2.427	-26.4	-2.415	-26.1
TotEmp	1.000	n/a	1.000	n/a
Theta_D_M			0.436	4.5

Business

	MNL		Structural Test	
Model		15		15T2
Observations		288		288
Log-likelihood		-1671.4		-1667.3
DOF		34		35
	Estimate	t-ratio	Estimate	t-ratio
LogCost	-1.158	-9.0	-1.268	-8.7
CarTime	-0.015	-2.9	-0.011	-2.1
CarPDist	-0.066	-5.0	-0.068	-5.0
PTIVtime	-0.013	-2.4	-0.013	-2.3
PTwttime	-0.007	-0.6	-0.005	-0.4
PTwktime	-0.003	-1.2	-0.003	-1.1
Transfers	0.000	n/a	0.000	n/a
WalkDist	-1.054	-6.1	-1.210	-5.8
CycleDist	-0.246	-3.0	-0.281	-3.2
1CrCmpCrD	-1.820	-4.0	-5.606	-1.4
FTwk38Walk	-2.551	-3.7	-6.815	-1.5
CarP	-8.034	-10.9	-16.128	-2.2
PT	-2.502	-4.9	-9.979	-1.3
Walk	-2.146	-3.1	-8.065	-1.4
Cycle	-7.608	-7.6	-18.531	-1.8
Intrazonal	-0.168	-0.5	-0.400	-1.2
Manchester	0.000	n/a	0.000	n/a
Trafford	-0.084	-0.3	-0.110	-0.4
Salford	-0.159	-0.5	-0.223	-0.7
Wigan	-0.218	-0.6	-0.307	-0.8
Bolton	0.185	0.6	0.180	0.6
Bury	-0.638	-1.4	-0.750	-1.6
Rochdale	0.456	1.5	0.410	1.3
Oldham	-0.011	0.0	-0.027	-0.1
Tameside	0.252	0.8	0.267	0.9
Stockport	-0.069	-0.3	-0.097	-0.4
Wilmslow	0.655	1.2	0.645	1.2
Glossop	-0.627	-0.7	-0.614	-0.6
Poynton	0.000	n/a	0.000	n/a
External	-1.946	-8.1	-1.982	-8.1
TotEmp	1.000	n/a	1.000	n/a
Theta_D_M			0.322	1.5

Education

	MNL	Structural Test
Model	27	27T2
Observations	4072	4072
Log-likelihood	-12617.9	-12595.1
DOF	39	40

	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.003	-3.6	-0.002	-2.9
LogCost	-0.508	-7.2	-0.560	-7.2
CarTime	-0.128	-20.5	-0.126	-19.6
CarPDist	-0.056	-6.4	-0.056	-6.3
PTIVtime	-0.041	-14.9	-0.042	-14.7
PTwttime	-0.020	-5.4	-0.024	-5.8
PTwktime	-0.026	-10.0	-0.026	-9.6
Transfers	0.000	n/a	0.000	n/a
WalkDist	-0.614	-36.3	-0.624	-34.6
CycleDist	-0.458	-6.9	-0.435	-6.4
CarCompCrD	-0.948	-6.0	-1.924	-4.4
PssOpt2HH	4.062	12.3	8.348	5.8
PssOpt3HH	3.227	14.2	6.616	6.0
MaleCarD	1.230	6.2	2.461	4.5
CarP_0_10	2.148	15.8	4.375	6.1
CarP_11_15	1.515	10.4	3.056	5.6
PT_0_10	-2.343	-11.8	-4.808	-5.7
FTstuPT	2.320	11.4	4.704	5.7
Walk_16_20	-1.298	-8.9	-2.569	-5.3
CarP	-6.765	-22.3	-13.430	-6.6
PT	-1.930	-6.5	-6.133	-4.5
Walk	-1.078	-4.5	-2.352	-4.9
Cycle	-5.323	-11.4	-11.430	-6.1
Intrazonal	0.055	0.4	-0.018	-0.1
CarPIZ	-0.079	-0.6	-0.104	-0.8
WalkIZ	0.623	4.5	0.715	4.9
CycleIZ	-2.623	-2.5	-2.398	-2.2
Manchester	0.000	n/a	0.000	n/a
Trafford	0.548	4.3	0.549	4.2
Salford	0.728	5.7	0.709	5.4
Wigan	0.709	3.6	0.687	3.4
Bolton	0.672	4.0	0.696	4.0
Bury	0.612	3.7	0.586	3.4
Rochdale	0.394	2.3	0.312	1.7
Oldham	0.637	4.3	0.602	3.9
Tameside	0.712	5.0	0.737	5.0
Stockport	0.806	7.6	0.773	7.1
Wilmslow	0.105	0.2	-0.011	0.0

Glossop	0.886	3.1	1.094	3.8
Poynton	1.591	4.8	1.609	4.5
External	-0.027	-0.1	-0.067	-0.3
EduEmp	1.000	n/a	1.000	n/a
Theta_D_M			0.551	71.9

Shopping

	MNL		Structural Test	
Model		48		48TB
Observations		2441		2441
Log-likelihood		-12239.7		-12196.2
DOF		49		51
	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.005	-4.6	-0.005	-4.6
LogCost	-0.609	-7.9	-0.561	-7.1
CarTime	-0.091	-13.9	-0.093	-13.9
CarPDist	-0.025	-3.9	-0.024	-3.8
PTIVtime	-0.035	-11.1	-0.033	-10.3
PTwttime	-0.051	-7.4	-0.055	-7.0
PTwktime	-0.042	-10.1	-0.045	-9.5
Transfers	-0.175	-1.0	-0.211	-1.2
WalkDist	-0.666	-23.9	-0.759	-22.2
CycleDist	-0.266	-3.8	-0.252	-3.7
1CrCmpCrD	-0.824	-5.8	-3.301	-3.0
2PlCmpCrD	-0.512	-1.8	-2.161	-1.7
PssOpt	2.317	17.6	8.991	3.4
CarP_0_10	0.885	4.0	3.265	2.6
MaleCarP	-1.119	-8.1	-4.462	-3.2
RetiredCrP	0.829	6.6	3.255	3.1
Ptstudent	-1.508	-3.0	-5.802	-2.3
WalkStudnt	-0.829	-2.8	-3.324	-2.2
CarP	-5.048	-22.9	-16.196	-3.7
PT	-2.618	-6.4	-11.175	-3.2
Walk	-1.912	-6.7	-7.669	-3.1
Cycle	-7.967	-10.7	-26.314	-3.7
Intrazonal	-0.302	-2.2	-0.298	-2.1
CarPIZ	-0.236	-1.3	-0.251	-1.3
WalkIZ	0.813	4.6	0.568	3.0
CycleIZ	1.871	2.5	2.253	2.8
Manchester	0.000	n/a	0.000	n/a
Trafford	-0.719	-6.1	-0.728	-5.9
Salford	-0.092	-0.8	-0.038	-0.3
Wigan	-0.735	-4.0	-0.730	-3.9
Bolton	-0.511	-3.4	-0.461	-3.0
Bury	-0.462	-2.9	-0.312	-1.9
Rochdale	-0.441	-2.7	-0.321	-1.9
Oldham	-0.309	-2.0	-0.341	-2.1
Tameside	0.409	3.0	0.451	3.3
Stockport	-0.032	-0.3	0.034	0.3
Wilmslow	1.500	7.2	1.558	7.4
Glossop	-0.255	-0.8	0.062	0.2
Poynton	1.107	3.1	0.973	2.4
External	-1.535	-7.8	-1.500	-7.5

	MNL		Structural Test	
TP_AA	3.019	2.9	4.147	1.9
TP_AI	4.486	4.5	6.140	2.1
TP_AP	0.000	n/a	0.000	n/a
TP_AO	-1.000	n/a	-1.000	n/a
TP_IA	1.299	1.1	1.868	1.0
TP_II	7.623	7.6	10.393	2.3
TP_IP	5.556	5.5	7.582	2.2
TP_IO	4.035	4.0	5.609	2.0
TP_PI	3.951	3.9	5.435	2.0
TP_PP	4.870	4.8	6.641	2.2
TP_PO	2.739	2.6	3.839	1.8
TP_OA	-1.000	n/a	-1.000	n/a
TP_OI	-1.000	n/a	-1.000	n/a
TP_OP	-1.000	n/a	-1.000	n/a
TP_OO	4.544	4.5	6.334	2.1
RetailEmp	1.000	n/a	1.000	n/a
Theta_D_TP			0.744	2.6
Theta_TP_M			0.339	2.1

Other Travel

	MNL		Structural Test	
Model		37		37TB
Observations		4816		4816
Log-likelihood		-30128.5		-30057.0
DOF		58		60
	Estimate	t-ratio	Estimate	t-ratio
LogCost	-0.549	-11.8	-0.583	-11.8
CarTime	-0.083	-26.9	-0.082	-24.9
CarPDist	-0.009	-3.6	-0.009	-3.7
PTIVtime	-0.034	-14.6	-0.033	-13.6
PTwttime	-0.039	-8.4	-0.043	-8.3
PTwktime	-0.029	-10.6	-0.031	-10.5
WalkDist	-0.512	-31.1	-0.541	-29.3
CycleDist	-0.280	-5.9	-0.280	-5.8
CarCompCrD	-0.404	-4.6	-2.308	-2.7
PssOpt2HH	1.515	13.8	8.237	3.3
PssOpt3HH	1.195	11.3	6.536	3.2
0to10CarP	1.514	12.1	8.173	3.3
MaleCarP	-0.646	-7.9	-3.514	-3.1
RetiredCrP	0.364	3.7	2.087	2.5
RetiredPT	0.550	4.8	2.950	2.7
0CarsPT	1.081	9.0	6.431	3.1
HmMancWAlk	0.285	2.7	0.708	1.2
CarP	-3.088	-26.3	-15.585	-3.4
PT	-0.415	-2.2	-16.503	-2.8
Walk	-1.450	-8.2	-8.908	-3.2
Cycle	-6.145	-13.3	-30.399	-3.5
Intrazonal	0.272	3.1	0.197	2.2
CarPIZ	0.120	1.1	0.103	0.9
WalkIZ	0.756	6.4	0.820	6.5
CycleIZ	0.999	2.1	1.269	2.5
Manchester	0.000	n/a	0.000	n/a
Trafford	-0.037	-0.5	-0.133	-1.6
Salford	-0.033	-0.4	-0.092	-1.1
Wigan	-0.326	-3.0	-0.400	-3.6
Bolton	0.033	0.4	0.025	0.3
Bury	-0.392	-3.5	-0.430	-3.8
Rochdale	-0.087	-0.8	-0.136	-1.2
Oldham	-0.305	-2.9	-0.311	-2.9
Tameside	0.167	1.9	0.143	1.5
Stockport	0.035	0.4	0.017	0.2
Wilmslow	-0.096	-0.4	0.058	0.3
Glossop	-0.488	-2.6	-0.288	-1.5
Poynton	0.682	3.1	0.779	3.3
External	-1.312	-12.7	-1.330	-12.7
TP_AA	0.876	3.0	2.387	2.4

	MNL		Structural Test	
TP_AI	2.190	8.6	6.088	3.6
TP_AP	0.000	n/a	0.000	n/a
TP_AO	-1.896	-3.0	-4.883	-2.4
TP_IA	0.095	0.3	0.448	0.5
TP_II	4.636	19.0	12.949	3.9
TP_IP	3.401	13.8	9.414	3.9
TP_IO	2.990	12.1	8.663	3.7
TP_PI	1.936	7.5	5.472	3.5
TP_PP	2.460	9.7	6.741	3.7
TP_PO	2.315	9.2	6.665	3.6
TP_OA	-1.658	-3.0	-4.156	-2.3
TP_OI	-0.157	-0.5	0.112	0.1
TP_OP	-3.029	-2.9	-7.909	-2.3
TP_OO	3.408	13.9	10.018	3.8
SizeMult	1.000	n/a	1.000	n/a
TotEmp	6.002	64.0	6.191	63.3
Theta_D_TP			0.368	4.1
Theta_TP_M			0.494	2.8

Appendix G: Pooled Models

Commute

		MNL		Structural Test		Longitudinal Test	
Model			36		36T2		36T2L
Observations			75278		75278		75278
Weighted Obs			674734.3		674734.3		674734.3
Log-likelihood			-402554.0		-402482.1		-398544.4
DOF			46		47		47
	Datasets	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	All	-0.002	-20.1	-0.002	-19.9	-0.011	-121.1
LogCost	All	-0.654	-51.2	-0.663	-50.6	0.017	3.6
CarTime	HI, RSI	-0.032	-50.8	-0.032	-49.8	-0.018	-44.5
CarPDist	HI	-0.057	-34.2	-0.058	-34.4	-0.114	-60.3
PTIVtime	HI, PT	-0.023	-50.9	-0.023	-49.4	-0.020	-42.0
PTwttime	HI, PT	-0.008	-12.1	-0.008	-12.0	-0.016	-19.5
PTwktime	HI, PT	-0.013	-23.1	-0.012	-22.2	-0.013	-25.1
Transfers	HI, PT	-0.191	-10.9	-0.192	-10.9	0.442	26.2
WalkDist	HI	-0.481	-69.2	-0.496	-67.6	-0.498	-67.4
CycleDist	HI	-0.252	-39.0	-0.255	-38.4	-0.256	-38.4
1CrCmpCrD	HI	-1.990	-55.2	-3.122	-19.9	-3.594	-17.6
2PlCmpCrD	HI	-1.565	-31.5	-2.451	-17.7	-2.840	-16.2
PssOpt2HH	HI	1.050	19.0	1.623	14.2	1.852	13.2
PssOpt3HH	HI	0.791	16.8	1.214	13.2	1.370	12.3
SEGAB_PT	HI	1.257	22.5	1.979	15.5	2.347	14.7
SEGC1_PT	HI	0.797	21.4	1.260	15.1	1.498	14.4
SEGDE_Walk	HI	0.498	13.4	0.732	11.2	0.820	10.5
PTwkWalk	HI	1.000	25.6	1.524	16.7	1.731	15.2
MaleCycle	HI	1.306	17.3	2.032	13.4	2.326	12.6
HmMancPT	HI	0.761	18.8	1.291	13.9	1.548	13.4
CarP	HI	-4.687	-78.6	-6.982	-22.8	-6.400	-16.1
PT	HI	-1.553	-28.8	-3.690	-13.0	-3.961	-10.6
Walk	HI	-3.064	-44.4	-5.067	-18.5	-3.535	-10.0
Cycle	HI	-6.006	-59.5	-9.173	-21.4	-8.111	-14.6
Intrazonal	HI, RSI A	-0.275	-7.7	-0.303	-8.3	0.520	16.2
CarPIZ	HI	-0.310	-4.1	-0.317	-4.2	-0.380	-4.9
WalkIZ	HI	0.810	15.2	0.800	14.6	-0.021	-0.4

		MNL		Structural Test		Longitudinal Test	
CycleIZ	HI	0.173	1.5	0.129	1.1	-0.683	-5.9
Manchester	All	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	All	-0.137	-8.0	-0.142	-8.3	-0.101	-7.5
Salford	All	-0.296	-16.4	-0.301	-16.5	-0.393	-25.9
Wigan	All	-1.047	-35.8	-1.067	-35.7	-1.287	-46.0
Bolton	All	-0.873	-36.4	-0.862	-35.7	-1.049	-47.6
Bury	All	-0.798	-28.8	-0.819	-29.0	-0.958	-38.0
Rochdale	All	-0.627	-24.4	-0.633	-24.3	-0.798	-35.5
Oldham	All	-0.334	-15.8	-0.336	-15.7	-0.380	-21.7
Tameside	All	-0.224	-11.5	-0.228	-11.5	-0.184	-12.1
Stockport	All	-0.133	-8.4	-0.128	-8.0	-0.071	-5.7
Wilmslow	All	0.019	0.5	0.002	0.1	-0.187	-5.6
Glossop	All	-0.961	-14.5	-0.883	-12.9	-0.718	-12.3
Poynton	All	0.456	5.6	0.440	5.3	0.027	0.4
External	All	-4.204	-154.7	-4.206	-154.5	-3.226	-127.8
TotEmp	All	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	RSI B	0.746	125.1	0.745	125.0	0.644	135.6
CDAfter	RSI A	0.747	173.7	0.746	173.5	1.395	99.0
PTBefore	PT B	0.902	64.4	0.904	64.1	0.744	70.1
PTAfter	PT A	0.700	72.4	0.703	71.9	0.669	74.2
Theta_D_M	HI			0.636	21.3	0.552	18.6
LambdaL	HI, A data					-0.021	-4.5

Employer's Business

		MNL		Structural Test		Longitudinal Test	
Model			9		9T2		9T2L
Observations			7248		7248		7332
Weighted Obs			60393.4		60393.4		60279.9
Log-likelihood			-42695.0		-42639.3		-42973.3
DOF			34		35		36
	Datasets	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	All	-0.001	-5.3	-0.001	-5.4	0.001	74.9
LogCost	All	0.000	n/a	0.000	n/a	0.000	n/a
CarTime	HI, RSI	-0.013	-8.3	-0.013	-7.9	-0.031	-119.6
CarPDist	HI	-0.136	-15.3	-0.144	-15.3	-0.116	-13.6
PTIVtime	HI	-0.009	-5.6	-0.007	-4.2	-0.009	-8.6
PTIVtimeIC	PT	0.004	4.8	0.004	4.8	0.003	3.3
PTwttime	HI, PT	-0.007	-5.8	-0.006	-5.5	-0.008	-5.5
PTwktime	HI, PT	-0.001	-3.2	-0.002	-3.5	-0.002	-4.2
Transfers	HI, PT	-0.641	-14.3	-0.641	-14.1	-0.888	-21.4
WalkDist	HI	-0.882	-20.3	-0.927	-19.5	-0.858	-19.3
CycleDist	HI	-0.225	-8.7	-0.257	-9.7	-0.247	-9.7
1CrCmpCrD	HI	-2.219	-14.6	-9.636	-3.2	-9.387	-5.3
FTwk38Walk	HI	-2.330	-11.2	-9.496	-3.1	-9.254	-5.1
CarP	HI	-0.878	-5.8	-13.326	-2.6	-13.182	-4.7
PT	HI	-2.427	-15.7	-14.674	-3.0	-14.816	-5.5
Walk	HI	3.627	19.3	-5.342	-1.4	-5.641	-2.7
Cycle	HI	-1.705	-6.0	-19.145	-2.7	-18.932	-4.8
Intrazonal	HI, RSI A	0.087	0.8	0.065	0.6	0.356	3.3
Manchester	All	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	All	0.122	2.6	0.131	2.8	0.161	3.7
Salford	All	-0.572	-9.4	-0.606	-9.8	-0.525	-8.9
Wigan	All	-1.097	-11.7	-1.220	-12.0	-1.160	-11.9
Bolton	All	-0.358	-6.0	-0.365	-6.0	-0.433	-7.4
Bury	All	-0.884	-9.6	-0.946	-9.8	-0.894	-9.8
Rochdale	All	-0.330	-4.8	-0.420	-5.8	-0.372	-5.3
Oldham	All	-0.408	-6.1	-0.426	-6.3	-0.309	-4.8
Tameside	All	0.109	2.0	0.116	2.2	0.215	4.2
Stockport	All	0.242	5.7	0.238	5.5	0.255	6.3
Wilmslow	All	-0.057	-0.5	-0.036	-0.3	-0.026	-0.2
Glossop	All	-0.096	-0.6	-0.030	-0.2	0.112	0.7
Poynton	All	-0.821	-2.1	-0.762	-1.9	-0.686	-1.8
External	All	-3.459	-67.1	-3.488	-67.1	-3.564	-71.4
TotEmp	All	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	RSI B	0.914	45.8	0.910	45.8	1.014	50.1
CDAfter	RSI A	1.041	53.4	1.039	53.7	1.115	63.4
PTBefore	PT B	1.097	21.4	1.087	21.5	1.105	21.2
PTAfter	PT A	0.984	23.3	0.979	23.3	1.004	23.6
Theta_D_M	HI			0.225	3.2	0.229	5.7
LambdaL	All					-0.637	-8.7

Education

		MNL		Structural Test		Longitudinal Test	
Model			7		7T2		7T2
Observations			9099		9099		9099
Weighted Obs			412613.9		412613.9		412613.9
Log-likelihood			-28579.1		-28543.8		-28510.1
DOF			43		44		45
	Datasets	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	All	-0.004	-8.5	-0.004	-7.6	-0.004	-33.7
LogCost	All	-0.312	-6.4	-0.346	-6.5	-0.255	-9.3
CarTime	HI, RSI	-0.147	-30.9	-0.146	-29.9	-0.146	-68.8
CarPDist	HI	-0.086	-10.7	-0.085	-10.5	-0.090	-12.3
PTIVtime	HI, PT	-0.042	-23.3	-0.042	-23.1	-0.042	-27.2
PTwttime	HI, PT	-0.021	-9.0	-0.024	-9.3	-0.024	-9.4
PTwktime	HI, PT	-0.022	-13.8	-0.023	-13.6	-0.023	-14.0
Transfers	HI, PT	0.000	n/a	0.000	n/a	0.000	n/a
WalkDist	HI	-0.606	-52.9	-0.612	-51.0	-0.614	-51.1
CycleDist	HI	-0.465	-8.9	-0.449	-8.4	-0.451	-8.5
CarCompCrD	HI	-0.975	-8.9	-1.756	-6.9	-1.596	-7.0
PssOpt2HH	HI	4.343	17.9	7.815	9.2	7.129	9.7
PssOpt3HH	HI	3.337	20.5	5.980	9.5	5.457	10.1
MaleCarD	HI	1.237	8.4	2.174	6.6	1.971	6.7
CarP_0_10	HI	2.454	24.4	4.364	10.0	3.982	10.6
CarP_11_15	HI	1.750	16.5	3.097	9.1	2.826	9.6
PT_0_10	HI	-2.114	-16.6	-3.825	-9.0	-3.484	-9.4
FTstuPT	HI	2.172	16.2	3.885	8.9	3.543	9.4
Walk_16_20	HI	-1.265	-12.8	-2.163	-8.4	-1.982	-8.7
CarP	HI	-6.629	-30.3	-11.913	-10.3	-10.695	-10.9
PT	HI	-2.205	-11.0	-5.292	-7.3	-4.733	-7.7
Walk	HI	-0.672	-4.1	-1.627	-5.7	-1.146	-5.1
Cycle	HI	-5.092	-14.4	-9.891	-9.1	-8.672	-9.3
Intrazonal	HI, RSI A	0.110	1.3	0.045	0.5	0.173	2.1
CarPIZ	HI	-0.230	-2.4	-0.248	-2.5	-0.291	-3.0
WalkIZ	HI	0.596	6.2	0.683	6.8	0.544	5.7
CycleIZ	HI	-2.936	-3.2	-2.771	-3.0	-2.916	-3.2
Manchester	All	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	All	0.724	8.8	0.724	8.6	0.730	8.7
Salford	All	0.765	8.8	0.787	8.9	0.791	8.8
Wigan	All	0.033	0.2	0.030	0.2	0.033	0.2
Bolton	All	0.476	4.1	0.489	4.1	0.499	4.2
Bury	All	0.562	4.8	0.539	4.5	0.507	4.2
Rochdale	All	0.311	2.7	0.233	1.9	0.286	2.3
Oldham	All	0.661	6.6	0.667	6.4	0.674	6.3
Tameside	All	0.892	9.5	0.915	9.4	0.942	9.6
Stockport	All	0.893	13.3	0.874	12.6	0.876	12.7
Wilmslow	All	0.834	4.1	0.764	3.5	0.741	3.4
Glossop	All	0.723	3.6	0.914	4.4	0.890	4.3

		MNL		Structural Test		Longitudinal Test	
Poynton	All	2.211	10.1	2.240	10.1	2.241	10.1
External	All	-0.296	-2.1	-0.331	-2.4	-0.308	-2.2
EduEmp	All	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	RSI B	0.472	12.1	0.474	12.1	0.477	12.4
CDAfter	RSI A	0.453	21.6	0.454	21.6	0.452	22.5
PTBefore	PT B	0.843	16.7	0.837	16.7	0.834	16.7
PTAfter	PT A	0.572	17.4	0.565	17.3	0.566	17.3
Theta_D_M	HI			0.551	10.7	0.604	11.5
LambdaL	All					-0.583	-6.5

Shopping

		MNL		Structural Test		Longitudinal Test	
Model			5		5B		
Observations			20298		20298		
Weighted Obs			320468.3		320468.3		
Log-likelihood			-96835.8		-96563.6		
DOF			53		55		
	Datasets	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	All	-0.003	-6.7	-0.003	-6.7		
LogCost	All	-0.668	-24.2	-0.646	-22.8		
CarTime	HI, RSI	-0.107	-45.6	-0.108	-45.4		
CarPDist	HI	-0.020	-6.9	-0.020	-6.9		
PTIVtime	HI, PT	-0.038	-33.1	-0.038	-32.1		
PTwttime	HI, PT	-0.041	-18.9	-0.041	-17.6		
PTwktime	HI, PT	-0.033	-24.2	-0.035	-23.3		
Transfers	HI, PT	-0.724	-11.5	-0.756	-11.8		
WalkDist	HI	-0.679	-61.0	-0.758	-56.7		
CycleDist	HI	-0.294	-11.3	-0.261	-9.8		
1CrCmpCrD	HI	-0.928	-15.4	-3.682	-7.4		
2PlCmpCrD	HI	-0.731	-7.0	-3.080	-5.5		
PssOpt	HI	2.380	42.5	9.288	8.3		
CarP_0_10	HI	0.841	9.5	3.329	6.3		
MaleCarP	HI	-1.112	-18.9	-4.508	-7.7		
RetiredCrP	HI	0.915	17.2	3.634	7.5		
Ptstudent	HI	-1.915	-8.6	-7.617	-6.0		
WalkStudnt	HI	-1.234	-10.0	-4.840	-6.4		
CarP	HI	-5.413	-59.3	-17.256	-9.0		
PT	HI	-3.653	-24.3	-12.323	-8.6		
Walk	HI	-2.029	-19.5	-7.857	-7.9		
Cycle	HI	-7.655	-29.9	-25.026	-9.1		
Intrazonal	HI, RSI A	-0.441	-8.8	-0.499	-9.7		
CarPIZ	HI	0.041	0.6	0.057	0.8		
WalkIZ	HI	0.779	11.7	0.680	9.5		
CycleIZ	HI	2.123	8.6	2.932	10.9		

		MNL		Structural Test		Longitudinal Test
Manchester	All	0.000	n/a	0.000	n/a	
Trafford	All	-0.156	-3.9	-0.116	-2.8	
Salford	All	-0.110	-2.5	-0.088	-1.9	
Wigan	All	-1.212	-16.2	-1.269	-16.4	
Bolton	All	-0.672	-11.4	-0.695	-11.4	
Bury	All	-0.517	-8.2	-0.415	-6.5	
Rochdale	All	-0.663	-10.4	-0.614	-9.1	
Oldham	All	-0.507	-9.0	-0.563	-9.6	
Tameside	All	0.642	14.2	0.607	13.1	
Stockport	All	0.183	4.7	0.205	5.2	
Wilmslow	All	1.143	13.6	1.240	15.1	
Glossop	All	0.068	0.5	0.276	2.1	
Poynton	All	1.054	6.9	0.915	5.2	
External	All	-2.734	-31.5	-2.743	-31.4	
TP_AA	HI	3.214	11.7	4.165	5.5	
TP_AI	HI	4.277	16.3	5.518	5.8	
TP_AP	HI	0.000	n/a	0.000	n/a	
TP_AO	HI	-1.000	n/a	-1.000	n/a	
TP_IA	HI	1.330	4.0	1.829	3.3	
TP_II	HI	7.389	28.7	9.448	6.3	
TP_IP	HI	5.292	20.4	6.794	6.1	
TP_IO	HI	3.739	14.2	4.897	5.5	
TP_PI	HI	3.887	14.7	5.038	5.7	
TP_PP	HI	4.788	18.4	6.148	6.0	
TP_PO	HI	3.075	11.4	4.045	5.3	
TP_OA	HI	-1.000	n/a	-1.000	n/a	
TP_OI	HI	-1.000	n/a	-1.000	n/a	
TP_OP	HI	-1.000	n/a	-1.000	n/a	
TP_OO	HI	4.332	16.6	5.672	5.6	
RetailEmp	All	1.000	n/a	1.000	n/a	
CDBefore	RSI B	0.896	45.8	0.894	45.5	
CDAfter	RSI A	0.611	75.5	0.611	74.8	
PTBefore	PT B	0.691	32.6	0.682	32.3	
PTAfter	PT A	0.520	30.9	0.513	30.6	
Theta_D_TP	HI			0.797	6.9	
Theta_TP_M	HI			0.314	5.3	
LambdaL	All					

Other Travel

		MNL		Structural Test		Longitudinal Test	
Model			11		11B		
Observations			37789		37789		
Weighted Obs			619971.7		619971.7		
Log-likelihood			-223569.1		-223020.7		
DOF			58		60		
	Datasets	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	All	0.000	n/a	0.000	n/a		
LogCost	All	-0.687	-41.7	-0.755	-40.5		
CarTime	HI, RSI	-0.087	-73.0	-0.084	-66.1		
CarPDist	HI	-0.010	-7.9	-0.011	-8.4		
PTIVtime	HI, PT	-0.033	-37.1	-0.030	-32.9		
PTwttime	HI, PT	-0.026	-17.1	-0.028	-16.8		
PTwktime	HI, PT	-0.033	-29.7	-0.036	-29.9		
Transfers	HI, PT	-0.739	-19.1	-0.813	-20.4		
WalkDist	HI	-0.526	-79.7	-0.556	-74.7		
CycleDist	HI	-0.347	-15.2	-0.335	-14.3		
CarCompCrD	HI	-0.304	-8.2	-7.348	-1.6		
PssOpt2HH	HI	1.426	30.3	31.691	1.6		
PssOpt3HH	HI	1.208	27.1	26.974	1.6		
0to10CarP	HI	1.586	29.9	34.724	1.6		
MaleCarP	HI	-0.581	-16.5	-12.977	-1.6		
RetiredCrP	HI	0.349	8.2	7.873	1.6		
RetiredPT	HI	0.771	16.5	15.767	1.6		
0CarsPT	HI	1.016	20.7	25.303	1.6		
HmMancWAlk	HI	0.288	6.8	2.800	1.5		
CarP	HI	-3.068	-61.8	-61.717	-1.6		
PT	HI	-0.693	-8.9	-75.916	-1.6		
Walk	HI	-1.551	-23.5	-33.926	-1.6		
Cycle	HI	-5.861	-31.6	-118.311	-1.6		
Intrazonal	HI, RSI A	-0.070	-1.9	-0.209	-5.6		
CarPIZ	HI	0.286	6.0	0.274	5.6		
WalkIZ	HI	0.802	16.7	0.962	18.8		
CycleIZ	HI	0.630	3.2	1.222	5.8		
Manchester	All	0.000	n/a	0.000	n/a		
Trafford	All	0.025	0.9	-0.033	-1.1		
Salford	All	-0.010	-0.4	-0.030	-1.0		
Wigan	All	-1.083	-24.6	-1.306	-28.1		
Bolton	All	-0.170	-4.7	-0.186	-5.1		
Bury	All	-0.591	-13.4	-0.630	-13.8		
Rochdale	All	-0.189	-4.5	-0.267	-6.2		
Oldham	All	-0.265	-6.8	-0.276	-6.9		
Tameside	All	0.336	9.9	0.325	9.4		
Stockport	All	0.076	2.7	0.057	2.0		
Wilmslow	All	0.363	5.0	0.587	8.5		

Glossop	All	-0.333	-4.0	-0.161	-1.9	
Poynton	All	0.435	4.4	0.555	5.1	
External	All	-2.708	-64.7	-2.760	-65.6	
TP_AA	HI	1.434	11.2	1.907	8.3	
TP_AI	HI	2.302	19.3	3.089	10.2	
TP_AP	HI	0.000	n/a	0.000	n/a	
TP_AO	HI	-2.945	-6.2	-3.874	-5.5	
TP_IA	HI	0.231	1.6	0.343	1.7	
TP_II	HI	4.827	42.3	6.494	11.4	
TP_IP	HI	3.527	30.6	4.728	11.1	
TP_IO	HI	3.137	27.1	4.280	10.6	
TP_PI	HI	2.017	16.8	2.725	9.6	
TP_PP	HI	2.636	22.4	3.522	10.6	
TP_PO	HI	2.580	22.0	3.508	10.3	
TP_OA	HI	-1.357	-5.8	-1.744	-5.2	
TP_OI	HI	-0.022	-0.1	0.070	0.3	
TP_OP	HI	-5.020	-3.9	-6.629	-3.7	
TP_OO	HI	3.757	32.7	5.147	10.7	
SizeMult	All	1.000	n/a	1.000	n/a	
ServEmp	HI	6.410	219.4	6.454	216.2	
CDBefore	RSI B	0.729	82.3	0.733	81.3	
CDAfter	RSI A	0.626	115.2	0.627	114.5	
PTBefore	PT B	0.445	40.2	0.438	40.0	
PTAfter	PT A	0.368	41.0	0.365	40.6	
Theta_D_TP	HI			0.751	6.4	
Theta_TP_M	HI			0.059	1.0	
LambdaL	All					

Appendix H: Freight Model Results

The freight results are presented in the following tables. The correlation values presented at the bottom of the table reflects the correlation between the linear cost and car time parameters.

LGV Destination Choice Models

	MNL		LogCost		Structural Test		Generalised Time		Longitudinal Test*	
Model		009		009_LC		013		014		016
Observations		12451		12451		12451		12451		12451
Weighted Obs		98868.9		98868.9		98868.9		98868.9		98868.9
Log-likelihood		-79633.0		-78781.3		-79604.2		-79772.2		-79767.5
DOF		18		19		19		17		18
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.007	-33.5	-0.002	-11.1	-0.007	-32.0				
CarTime	-0.035	-13.9	-0.001	-0.3	-0.039	-15.0				
LogCost			-1.527	-46.6						
GenTime							-0.074	-69.6	-0.083	-28.8
Manchester	0.000	n/a	0.000	n/a	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.273	6.9	0.235	6.0	0.269	6.8	0.211	5.5	0.220	5.5
Salford	0.321	9.4	0.229	6.8	0.322	9.4	0.291	8.6	0.310	8.8
Wigan	0.631	7.3	0.474	5.6	0.640	7.4	0.462	5.4	0.499	5.8
Bolton	0.334	5.0	0.450	6.9	0.326	4.9	0.045	0.7	0.084	1.3
Bury	0.496	7.6	0.576	9.1	0.497	7.6	0.348	5.4	0.380	5.8
Rochdale	0.569	9.3	0.608	10.2	0.569	9.3	0.437	7.3	0.468	7.7
Oldham	0.884	23.8	0.910	25.0	0.879	23.7	0.834	22.8	0.866	22.6
Tameside	0.907	21.1	0.963	22.9	0.906	21.1	0.869	20.4	0.894	20.6
Stockport	0.857	27.5	0.786	25.3	0.849	27.2	0.774	25.4	0.799	24.6
Wilmslow	-0.131	-0.9	0.055	0.4	-0.130	-0.9	-0.210	-1.5	-0.206	-1.4
Glossop	1.022	4.0	0.925	3.7	1.048	4.1	1.073	4.3	1.102	4.4
Poynton	1.399	5.2	1.488	5.7	1.408	5.3	1.297	4.9	1.336	4.9
Extzones	-0.295	-4.3	-1.030	-14.7	-0.300	-4.3	-0.956	-16.6	-0.916	-17.0
TP_IP	2.151	56.3	2.214	59.6	16.877	1.5	1.976	54.6	2.060	45.1
TP_PM	0.561	13.3	0.600	14.7	4.914	1.5	0.486	11.7	0.514	11.8
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	0.875	94.8	0.951	104.8	0.877	94.8	0.901	96.7	0.826	36.4
Theta_D_TP	1.000	n/a	1.000	n/a	0.140	1.5	1.000	n/a	1.000	n/a
LambdaL									-0.198	-3.0

	MNL	LogCost	Structural Test	Generalised Time	Longitudinal Test*
correlation	-0.774	-0.568	-0.726		*did not converge
VOT	2.88	depends on cost	3.30	11.55	11.55
t-VOT	10.3		10.9	(WebTAG)	(WebTAG)

LGV Origin Choice Models

	MNL		LogCost		Structural Test		Generalised Time		Longitudinal Test	
Model		009		009_LC		013		014		016
Observations		12451		12451		12451		12451		12451
Weighted Obs		98868.9		98868.9		98868.9		98868.9		98868.9
Log-likelihood		-70620.4		-70187.4		-70597.8		-70690.7		-71127.3
DOF		18		19		19		17		18
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.007	-28.7	-0.002	-8.2	-0.007	-27.1				
CarTime	-0.052	-19.8	-0.029	-11.6	-0.056	-20.5				
LogCost			-1.191	-31.4						
GenTime							-0.080	-72.1	-0.058	-55.0
Manchester	0.000	n/a	0.000	n/a	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.574	18.4	0.594	19.4	0.570	18.3	0.567	18.3	0.657	19.9
Salford	0.793	15.1	0.826	15.9	0.792	15.1	0.759	14.6	0.879	16.0
Wigan	0.343	1.1	0.171	0.6	0.349	1.2	0.212	0.7	-0.214	-0.7
Bolton	-0.113	-0.5	-0.114	-0.6	-0.123	-0.6	-0.313	-1.5	-0.401	-1.9
Bury	-0.197	-0.9	-0.204	-0.9	-0.194	-0.8	-0.346	-1.5	-0.396	-1.7
Rochdale	-0.509	-2.1	-0.490	-2.0	-0.508	-2.1	-0.661	-2.7	-0.784	-3.0
Oldham	-0.036	-0.3	0.048	0.5	-0.029	-0.3	-0.076	-0.7	-0.054	-0.5
Tameside	0.884	27.8	0.917	29.4	0.879	27.6	0.868	27.5	0.998	29.5
Stockport	0.838	27.5	0.783	25.8	0.833	27.3	0.784	26.2	0.757	22.9
Wilmslow	-0.395	-3.0	-0.371	-2.9	-0.392	-3.0	-0.455	-3.5	-0.700	-5.1
Glossop	1.152	11.6	1.039	10.6	1.176	11.9	1.198	12.2	1.031	9.9
Poynton	1.200	6.6	1.190	6.7	1.204	6.6	1.141	6.3	0.899	4.6
Extzones	-1.751	-22.6	-2.495	-31.2	-1.759	-22.6	-2.148	-30.7	-2.812	-39.9
TP_IP	2.100	55.6	2.131	57.6	10.964	2.0	2.004	54.7	2.274	57.4
TP_PM	0.582	13.8	0.597	14.5	3.196	1.9	0.541	12.9	0.355	7.6
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	0.871	93.6	0.924	96.6	0.869	94.8	0.879	93.6	0.699	77.0
Theta_D_TP	1.000	n/a	1.000	n/a	0.214	2.0	1.000	n/a	1.000	n/a
LambdaL									0.103	7.9

	MNL	LogCost	Structural Test	Generalised Time	Longitudinal Test
correlation	-0.778	-0.486	-0.787		
VOT	4.52	depends on cost	5.10	11.55	11.55
t-VOT	12.4		12.3	(WebTAG)	(WebTAG)

OGV Destination Choice Models

	MNL		LogCost		Structural Test		Generalised Time		Longitudinal Test*	
Model		007		007_LC		010		014		016
Observations		5219		5219		5219		5219		5219
Weighted Obs		41603.92		41603.92		41603.92		41603.92		41603.92
Log-likelihood		-33448.0		-32986.1		-33438.4		-33448.0		-33447.6
DOF		18		19		19		17		18
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.002	-14.3	0.000	-2.3	-0.002	-13.7				
CarTime	-0.031	-9.2	0.001	0.4	-0.033	-9.5				
LogCost			-1.520	-34.2						
GenTime							-0.030	-28.3	-0.029	-26.1
Manchester	0.000	n/a	0.000	n/a	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.445	7.6	0.469	8.1	0.444	7.6	0.447	11.5	0.441	7.6
Salford	0.378	7.3	0.258	5.0	0.378	7.3	0.378	11.2	0.373	7.2
Wigan	0.102	0.8	0.276	2.3	0.116	1.0	0.104	1.2	0.101	0.9
Bolton	-0.251	-2.5	0.144	1.5	-0.248	-2.4	-0.246	-3.8	-0.255	-2.6
Bury	0.094	1.0	0.411	4.3	0.101	1.0	0.096	1.5	0.090	0.9
Rochdale	0.367	4.3	0.645	7.7	0.373	4.4	0.368	6.1	0.360	4.4
Oldham	0.751	12.9	0.884	15.3	0.752	12.9	0.751	20.5	0.742	12.7
Tameside	0.519	6.7	0.646	8.5	0.522	6.7	0.519	12.1	0.515	6.7
Stockport	0.627	11.7	0.667	12.5	0.627	11.6	0.629	20.6	0.621	11.7
Wilmslow	-0.252	-1.2	0.031	0.1	-0.243	-1.2	-0.252	-1.8	-0.256	-1.2
Glossop	0.874	2.6	0.964	2.9	0.904	2.7	0.870	3.5	0.868	2.7
Poynton	0.057	0.1	0.349	0.5	0.066	0.1	0.057	0.2	0.052	0.1
Extzones	-1.219	-12.5	-1.333	-14.8	-1.197	-12.2	-1.208	-20.9	-1.220	-16.5
TP_IP	2.284	38.6	2.347	40.7	7.349	2.1	2.289	63.1	2.259	35.8
TP_PM	0.253	3.6	0.293	4.3	1.034	1.8	0.255	6.2	0.250	3.6
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	0.890	59.3	0.962	66.7	0.893	59.1	0.889	95.3	0.913	36.0
Theta_D_TP	1.000	n/a	1.000	n/a	0.330	2.2	1.000	n/a	1.000	n/a
LambdaL									0.160	1.2
correlation	-0.736				-0.748				*did not converge	
VOT	10.70		n/a		11.68		10.18		10.18	
t-VOT	6.0				6.0		(WebTAG)		(WebTAG)	

OGV Origin Choice Models

	MNL		LogCost		Structural Test*		Generalised Time		Longitudinal Test*	
Model	007		007_LC		010		014		016	
Observations	5219		5219		5219		5219		5219	
Weighted Obs	41603.92		41603.92		41603.92		41603.92		41603.92	
Log-likelihood	-29217.9		-28872.1		-29195.0		-29218.1		-29261.2	
DOF	18		19		19		17		18	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Cost	-0.002	-17.8	-0.00023	-1.6	-0.002	-15.6				
CarTime	-0.043	-12.5	-0.014	-4.2	-0.051	-14.2				
LogCost			-1.515	-28.9						
GenTime							-0.041	-38.9	-0.013	-765.2
Manchester	0.000	n/a	0.000	n/a	0.000	n/a	0.000	n/a	0.000	n/a
Trafford	0.750	16.4	0.749	16.7	0.735	16.1	0.751	16.5	0.669	15.9
Salford	1.127	16.2	1.162	16.8	1.116	16.0	1.129	16.3	0.979	15.0
Wigan	-0.001	0.0	-0.005	0.0	0.031	0.1	0.002	0.0	-0.143	-0.3
Bolton	-1.404	-2.6	-1.225	-2.3	-1.425	-2.7	-1.395	-2.6	-1.652	-3.2
Bury	-0.261	-0.8	-0.151	-0.5	-0.270	-0.8	-0.256	-0.8	-0.500	-1.6
Rochdale	-0.322	-1.0	-0.182	-0.6	-0.327	-1.1	-0.316	-1.0	-0.515	-1.8
Oldham	-0.157	-0.9	-0.046	-0.3	-0.139	-0.8	-0.157	-0.9	-0.258	-1.7
Tameside	0.690	13.9	0.747	15.4	0.677	13.6	0.691	14.0	0.574	12.7
Stockport	0.624	13.0	0.598	12.6	0.607	12.7	0.627	13.2	0.491	11.5
Wilmslow	-1.048	-4.1	-0.981	-3.9	-1.042	-4.1	-1.046	-4.1	-1.018	-4.4
Glossop	0.940	6.3	0.815	5.5	0.985	6.6	0.935	6.3	0.700	5.2
Poynton	1.283	5.0	1.283	5.1	1.297	5.1	1.283	5.0	1.009	4.5
Extzones	-2.039	-19.1	-2.621	-24.4	-2.039	-19.0	-2.027	-19.5	-2.253	-24.2
TP_IP	2.222	37.6	2.285	39.4	618.659	1.6	2.229	38.8	1.895	34.1
TP_PM	0.245	3.5	0.289	4.2	96.366	1.5	0.248	3.5	-0.111	-1.7
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a
CDBefore	0.859	61.0	0.928	64.2	0.858	61.9	0.859	61.0	1.140	47.2
Theta_D_TP	1.000	n/a	1.000	n/a	0.004	1.6	1.000	n/a	1.000	n/a
LambdaL									6.156	26.3

correlation	-0.696	-0.437	-0.714		*did not converge
VOT	10.90	depends on cost	14.57	10.18	10.18
t-VOT	7.9	0.0	8.0	(WebTAG)	(WebTAG)