RAND EUROPE

A new travel demand model for London

Estimation of the mode and destination choice models

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Preface

RAND Europe, working in collaboration with Jacobs, SYSTRA and Mott MacDonald, has been commissioned by Transport for London (TfL) to develop a new strategic travel model for London, termed the New Demand Model (NDM). This will be used to develop strategic land use and transport policy scenarios to assist with prioritisation and supporting the case for sustained investment of billions of pounds in London's transport systems. The new model is expected to enhance TfL's strategic modelling capability and reflect recent behavioural changes identified by the 'Drivers of Demand' study in London.

Jacobs is the lead consultant managing the overall delivery and in charge of tasks associated with the implementation of the final model and the integration of TfL assignment models. The segmentation review and recommendations were provided by Mott MacDonald, with SYSTRA being responsible for the calibration and testing of the resultant model. RAND Europe was responsible for the model estimation task, which involved developing models of travel frequency and mode-destination choice.

This report documents the development of mode-destination choice models for the NDM. While the primary audience for this report is TfL, it may be of wider interest for transport researchers and transport planners involved in demand forecasting and strategic planning. The report is aimed at audiences familiar with travel demand modelling.

One other RAND Europe report has been produced for this study, documenting the development of models of travel frequency. This report is not currently in the public domain.

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Executive summary

This report documents the development of the mode-destination models that form part of Transport for London's New Demand Model (NDM).

Modelling assumptions

The models have been developed using a tour-based approach. The key unit of analysis is the home-based (HB) tour, which is a series of linked trips starting and finishing at the travellers' home. For each trip chain a primary destination (PD) is identified that defines the purpose of the tour.

Two types of non-home-based (NHB) travel have been represented: firstly, PD-based tours that are a series of linked trips starting and finishing at the same PD, for example if an individual makes a trip out to the shops and then travels back to work during their work day; secondly, NHB detours made during the outward or return legs of HB tours, for example if an individual makes a diversion on the way home from work to pick up a child from school.

The mode-destination models have been developed to represent a 2011 base year. The process used to identify the samples of HB tours and NHB trips from London Travel Diary Survey (LTDS) data is termed 'tour building' and is documented in full in Appendix A.

Eight different purposes have been distinguished for HB travel:

1. Commute
2. Business
3. Primary education (children aged 5 to 11)
4. Secondary education (children aged 12 to 16)
5. Tertiary education (adults aged 17 and above)
6. Shopping
7. Escort
8. Other travel.

Six purposes have been distinguished for NHB travel:

1. Work-related (WR) tours made during WR HB tours
2. Non-work-related (NWR) tours made during WR HB tours
3. NWR tours made during NWR HB tours
4. WR detours made during WR HB tours
5. NWR detours made during WR HB tours
6. NWR detours made during NWR HB tours.

Seven modes are represented in the mode-destination models:

1. Car driver
2. Car passenger
3. Rail
4. Bus
5. Taxi
6. Cycle
7. Walk.

Four time periods have been distinguished in the models:

1. AM-peak, 07:01–10:00
2. Inter-peak, 10:01–16:00
3. PM-peak, 16:01–19:00
4. Off-peak, 19:01–07:00.

A total of 1,729 zones covering the whole of Great Britain are represented in the NDM zone system, 1,295 of which cover the study area inside the M25 boundary. In the commute model, which was developed first, travel to all 1,729 destination zones was represented. For all of the other travel purposes, only travel originating and ending in the study area was included in the model estimations. External destinations were dropped because better-quality models were obtained when external destinations were excluded, and in particular dropping external destinations helped to increase cost sensitivity in the models. The full choice between both internal and external destinations will be represented in the model implementation.

Data

The LTDS provides data on observed mode-destination choices alongside the person and household information required for the specification of segmentation variables. LTDS data from 2010–2012 have been used to represent the 2011 base year, with data collected during the Olympic period excluded from the analysis on TfL's advice. Only weekday records were retained in the analysis and therefore the mode-destination models that have been developed represent travel on an average weekday.

Highway level-of-service (LOS) data were supplied from TfL's London Highway Assignment Model (LoHAM). LoHAM works with a November 2012 base and it has been assumed that the LoHAM assignments can be taken to be representative of 2011 travel conditions. The LoHAM data were supplemented with toll information for the Congestion Charge and Dartford Crossing as well as parking cost information taken from the parking model. Taxi costs have been calculated by applying per kilometre rates supplied by TfL to LoHAM distance skims.

Public transport (PT) LOS data were taken from TfL's Railplan assignment model, representing a 2011 base year. Although the version of the Railplan used assigns all modes as a single user class assignment, two sets of LOS skims were made for the purposes of the estimation. For the rail mode-destination mode, National Rail/London Overground, Tube, DLR, Tram and Bus PT modes are represented and at least one rail mode must be used for rail to be available as an alternative. For the bus mode-destination mode, assignments were made where bus was the only PT mode available.

PT fare discounts for commute and business have been applied for commute and business travel using fixed factors taken from the previous strategic model for London, LTSv7.1. Child, student and older person discounts have been applied as a function of the age and status of the individual.

Cycle and walk LOS data came from TfL's CYNEMON assignment model, representing a 2014 base year. As all major cycle superhighway schemes were introduced post 2014, it has been assumed that the CYNEMON assignments can be taken to be representative of 2011 travel conditions.

Population, employment and education enrolment data were supplied by TfL and used as attraction variables in the mode-destination modelling.

Model specification

The mode-destination alternatives represented in the models are defined by the combination of the seven modes and the 1,729 destination zones, through as noted above for all purposes except commute only the 1,295 internal destination zones are available in the estimations. Mode-destination alternatives are represented as available if there is a non-zero attraction variable and, for some modes, if a mode-specific availability condition is satisfied. Specifically, car driver is only available if the traveller holds a licence and there is at least one car in the household, and the PT modes are only available if the LOS data indicate a non-zero PT in-vehicle time for travel to the destination.

Attraction variables have been used to represent the attractiveness of competing destination alternatives. The attraction variables tested for each purpose are based on RAND Europe's experience of developing other model systems, in particular the PRISM West Midlands and Sydney model systems.

The (monetary) cost formulations used in the mode-destination models incorporate cost damping, i.e. the marginal impact of cost on utility reduces with increasing cost. The starting point for the model development was to estimate separate linear and log cost terms, and if this did not yield acceptable models to then introduce a 'gamma' formulation that imposes a combination of linear and log cost, with different values of gamma giving different relative weights to the linear and log cost components.

For non-business purposes, car cost sharing between car drivers and car passengers is represented so that predicted occupancy levels are sensitive to changes in car costs. Model tests were undertaken for each purpose to determine the relative share of car costs borne by car drivers and car passengers based on the overall fit to the data. For business purposes, it is assumed that car costs will be reclaimed from the employer, so no car sharing was represented.

Variation in cost sensitivity with income was investigated by interacting the cost sensitivity parameters with income bands. Ten different household income bands were recorded in the LTDS data, and so the approach followed was to start by testing separate cost sensitivity bands for each of the ten income bands and then aggregate bands that were not statistically different from one another. This approach was repeated until each cost sensitivity parameter was statistically different from its immediate neighbours.

The starting point for the LOS specification searches was to estimate separate model parameters for each LOS component and separate linear and log cost parameters for monetary cost components. Car driver, car passenger, cycle, walk and taxi models were modelled as being available for intrazonal tours, i.e. tours with the same origin and destination zone, whereas PT modes were modelled as unavailable for intrazonal tours.

For walking and cycling, the model specification tested whether the overall preference for cycle and the disutility of generalised cycle distance varied between High Cycle Propensity (HCP) and Low Cycle Propensity (LCP) groups.

A range of person and household segmentations were tested in the model development work, including the key segmentation of car availability, which was specified as a function of individual licence holding, household licence holding and household car ownership. The segments that were tested were specified in the separate segmentation task.

Structural tests were undertaken to determine the relative sensitivity of main mode and destination choice, and to test for evidence of sub-mode nests for active modes, i.e. cycle and walk, and for PT modes, i.e. rail and bus.

Nested logit model results

For the commute model, it was possible to estimate separate linear and log cost terms, and the linear cost terms were segmented by three household income bands which means that cost sensitivity and therefore implied values of time vary by income band. For the home–business model, a 'gamma' formulation model was used to give a mixture of linear and log cost effects, with cost sensitivity terms segmented by two household income bands.

No costs were represented in the home–primary and home–secondary education models since car driver is not modelled and school children are eligible for free bus and rail travel. For home–tertiary education, separate linear and log cost parameters were estimated but there is no segmentation of cost sensitivity by income band.

For the home–shopping, home–escort and home–other travel models, it was not possible to estimate linear and log cost terms or models using a gamma cost formulation that yielded plausible values of time (VoTs). Given these difficulties, cost sensitivity information was transferred from the commute model, thus ensuring that the VoTs for these purposes were segmented by household income band.

For five of the six NHB models, it was not possible to estimate plausible cost sensitivity parameters and therefore VoTs were imported from WebTAG. The one exception was the work–work detour model, where a log-cost formulation has been used.

The car cost sharing tests for home–based purposes found that sharing factors of 0.25 gave the best fit to the data, implying that car passengers do pay some car costs but drivers pay a much larger share. For three of the NHB purposes sharing factors of 1 were identified, implying that car costs are shared equally between drivers and passengers, whereas for the other–other tour model a sharing factor of 0.5 was identified, implying that drivers pay a larger share of the costs than passengers. As noted above, no cost sharing tests were undertaken for business purposes.

With the exception of the home–other model, the parking search time terms were insignificant and therefore were not retained in the final model specifications. However, monetary parking costs are part of the car cost term for all travel purposes where car driver is modelled and therefore the models remain sensitive to parking cost changes.

A series of model tests for HB purposes were undertaken to determine the appropriate specification for the PT LOS terms. The base specification used separate parameters for rail in-vehicle time (IVT), bus

IVT, crowding time, access/egress time, wait time and boardings. An issue with the base specification was that crowding was wrongly signed across all purposes. A series of different specifications were then tested in search of a plausible representation of crowding that minimised the adverse impact on other model parameters.

For all of the HB purposes except home–escort, as well as for work–work detours, the selected model specification estimated separate bus and rail IVT parameters plus a PT out-of-vehicle time (OVT) term that included crowding.

For home–escort, and for all of the NHB purposes except work–work detours, the selected model specification estimated a rail generalised time term and a bus generalised time term, both of which include IVT, OVT components and crowding.

As noted above, tests were undertaken to investigate differences in preferences for cycling between HCP and LCP groups. For all of the HB purposes except secondary education, differences in the overall preference for cycling between HCP and LCP groups have been identified, reflecting greater preference for cycling in the HCP group. Furthermore, for commuting, business and tertiary education, differences in the sensitivity to generalised cycle distance between HCP and LCP groups have been identified, with lower sensitivity to increased generalised cycle distance for people in the HCP group. For the NHB purposes where sample sizes are smaller, no significant HCP effects were identified in the models.

A number of segmentation effects have been identified in the HB models, representing variation in preferences across car availability, gender, age, employment status, occupation, PT pass ownership, disability, household income and household type segments. In the NHB models, variations in preferences have been captured by HB tour mode, car availability, age, employment status and occupation segments.

The car availability parameters are particularly important in representing differences in mode share, in particular capturing differences in the car driver share between 'free car use' segments where every licence holder can drive if they choose and 'car competition' segments where there are more licence holders than cars and the probability of choosing car driver is lower. The probability of travelling as a car passenger is much higher in households where there is a car and at least one adult owns a licence.

Both the commute and home–business models capture higher rail use to high employment density areas using an employment density term. Furthermore, the home–business model includes a positive rail constant that is applied for all zones in the London Congestion Charge Zone area.

A number of population density terms have been added to the home–shopping, home–escort and home–other model specifications. These terms capture differences in mode use according to the population density at either the origin or the destination, specifically higher use of PT and walk modes in higher population density areas.

The structural tests included tests for sub-mode nesting for PT modes and active modes. The only purpose where a significant PT nest was identified was commute, and here the final model structure was main modes above simultaneous PT modes and destinations. No significant active mode nests were identified for any of the model purposes.

For home–tertiary education, work–work detours and other–other detours, the mode-destination nesting results indicated a multinomial nesting structure with mode and destination choices equally sensitive to changes in utility. For all other model purposes, modes above destination structures were identified which imply that destination choice is more sensitive to utility changes than mode choice. This structure is consistent with WebTAG guidance.

Nested logit validation

The models were validated by examining the implied VoTs, running model elasticities, comparing observed and predicted tour length distributions at the all-mode level and by comparing observed and predicted tour lengths by mode.

The commute and home–business VoTs validate well against WebTAG guidance for car driver and bus, with lower VoT values for rail due to the small rail IVT parameters. For the home–shopping, home–escort and home–other travel models, the implied VoTs are lower than WebTAG guidance for all modes, which is a consequence of transferring the commute cost function to purposes with lower mean trip lengths. The implication of low VoTs for model application is relatively high sensitivity to changes in cost for those modes with low VoTs relative to sensitivity to changes in in-vehicle time. However, the model elasticity tests found no evidence that the high cost sensitivity associated with low VoTs has resulted in high elasticities to fuel cost and fare changes.

The model elasticity validation showed the models to be slightly less elastic than WebTAG guidance to changes in fuel cost and PT fare. The low elasticities of discretionary travel purposes (home–shopping, home–escort and home–other) were key to this result and the low elasticities for these purposes are also related to the transfer of the commute cost function. This leads to our recommendation to revisit the model specifications for these journey purposes in any future estimation work. The implication for the model application is that the model is somewhat inelastic to changes in fuel cost and PT fares, particularly for discretionary travel purposes, and furthermore for discretionary travel purposes the sensitivity to changes in in-vehicle time is also on the low side. Thus the predicted impact of policy interventions that result in cost and/or time changes may be somewhat lower than anticipated.

A comparison of observed and predicted tour length distributions at the all-mode level demonstrated a good match between predicted and observed data for all purposes. In most cases there is a good correspondence between observed and predicted mean tour lengths by mode, though in some instances significant differences are observed, particularly for the NHB purposes where the estimation sample sizes are smaller such that the mean observed value may be calculated from a small sample size and therefore subject to greater uncertainty.

Cross-nested logit models

The original intention of this project was to develop cross-nested logit (CNL) models to reflect substitution patterns better than in nested logit (NL) models. In the modes above destinations NL structure identified for the majority of purposes, destinations are nested together, reflecting greater substitution between destinations than between modes. However, in an NL structure if a particular mode-destination alternative is improved, demand is drawn from other modes equally over available destination alternatives and this substitution pattern can give rise to counter-intuitive results. This is because in reality we would expect greater substitution from destination alternatives closer to the destination alternative that is improved than from more distant destination alternatives. CNL models provide more realistic substitution patterns, to be represented by associating each mode-destination alternative with both a mode and a destination nest.

Tis report illustrates the difference between NL and CNL structures for a simple two-mode and two-destination zone example, and then goes on to set out a detailed mathematical formulation for the CNL approach.

To estimate the CNL parameters, the NL parameters were held fixed and then a grid-search procedure was applied to test different values for the CNL parameters. For each set of CNL parameters tested, the fit to the mode-destination choices observed in the LTDS data was calculated and then the direction of improvement or deterioration in model fit was used to determine the next grid-search test.

The grid-search for commute did not identify any CNL models that gave a better fit to the data than the NL model parameters. Investigations were undertaken to understand why the fit of the CNL models was worse than the NL models, and runs were made where the mode constants were re-estimated in the CNL models to match the observed mode shares. This step recovered some of the loss of likelihood relative to the NL results but the overall fit remained worse. Note that it was not possible to fully estimate all of the NL model parameters in the CNL context using the grid-search approach adopted for this study.

For home–other travel, the picture was different. The grid search did identify CNL results that gave some improvement in fit relative to the NL models. However, these models were very close to the NL models such that in practical terms the substitution patterns in the models would be indistinguishable from those in the NL model structure. In this case there would be no benefit in implementing the more complex CNL models.

It was concluded that using the grid-search method it was not possible to identify CNL models suitable for policy testing that yielded a significant improvement in fit and more plausible substitution patterns relative to the NL models. The final NL models have therefore been taken forward for implementation. In the longer term, our recommendation is that TfL investigates the potential of software packages that allow a formal estimation of CNL models, rather than estimating them using a grid-search procedure with the NL model parameters held fixed. Software options for further investigation include an enhanced version of ALOGIT, NLOGIT, Biogeme, Larch, Ox and R.

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Abbreviations

CNL	Cross-Nested Logit
DLR	Docklands Light Railway
EB	Employer's Business
HB	Home-Based
HCP	High Cycle Propensity
IVT	In-Vehicle Time
LCP	Low Cycle Propensity
LoHAM	London Highway Assignment Model
LOS	Level of Service
LTDS	London Travel Diary Survey
MD	Mode-Destination
NDM	New Demand Model
NHB	Non-Home-Based
NL	Nested Logit
NWR	Non-Work-Related
OD	Origin-Destination
OVT	Out-of-Vehicle Time
PD	Primary Destination
PT	Public Transport
SD	Secondary Destination
WR	Work-Related
VoT	Value of Time

1. Introduction

This report documents the development of the mode-destination (MD) models that form part of Transport for London's New Demand Model (NDM). It is structured as follows.

Chapter 2 sets out the key modelling assumptions, with an explanation of the modelling approach, definitions of the model base year, travel purposes, modes and time periods, and a summary of the model zone system.

Chapter 3 details the model inputs. It describes the London Travel Diary Survey (LTDS) data, which records travellers observed mode and destination choices, the level-of-service data used to represent travel conditions on the highway and public transport networks, and the trip attraction data used to represent the attractiveness of competing destination zones.

Chapter 4 describes the nested logit model specifications. It sets out the mode-destination alternatives that are represented in the choice model, the attraction variables that have been used for each model purpose and how cost sensitivity has been handled in the models. It also describes how the level-of-service terms have been represented in the model specification, explains the use of a cycling propensity approach, and sets out the structural tests used to capture differences in the sensitivity of different choices to changes in utility.

Chapter 5 presents the nested logit model results, with sections covering how monetary cost has been treated, the representation of level-of-service terms, the cycle propensity results, a summary of the segmentation terms identified, a description of the origin and destination effects that have been identified and a summary of the results from the structural tests.

Chapter 6 documents the validation of the nested logit models. It includes comparisons of the implied values of time and model elasticities against WebTAG guidance values, and offers analysis of the models' ability to replicate observed trip length distributions.

Chapter 7 presents the cross-nested logit model estimations.

Finally, Chapter 8 summarises the estimation work and gives some recommendations for further work.

2. Modelling assumptions

This chapter sets out the key modelling assumptions used to define the scope of the disaggregate models of mode-destination choice that have been developed for the NDM. The tour-based modelling approach is first outlined, describing how travel has been represented using a combination of home-based tours, non-home-based tours and non-home-based detours. Then the model base year, travel purposes, modes, times of day and zone system are specified, drawing on analysis of LTDS data.

2.1. Tour-based approach

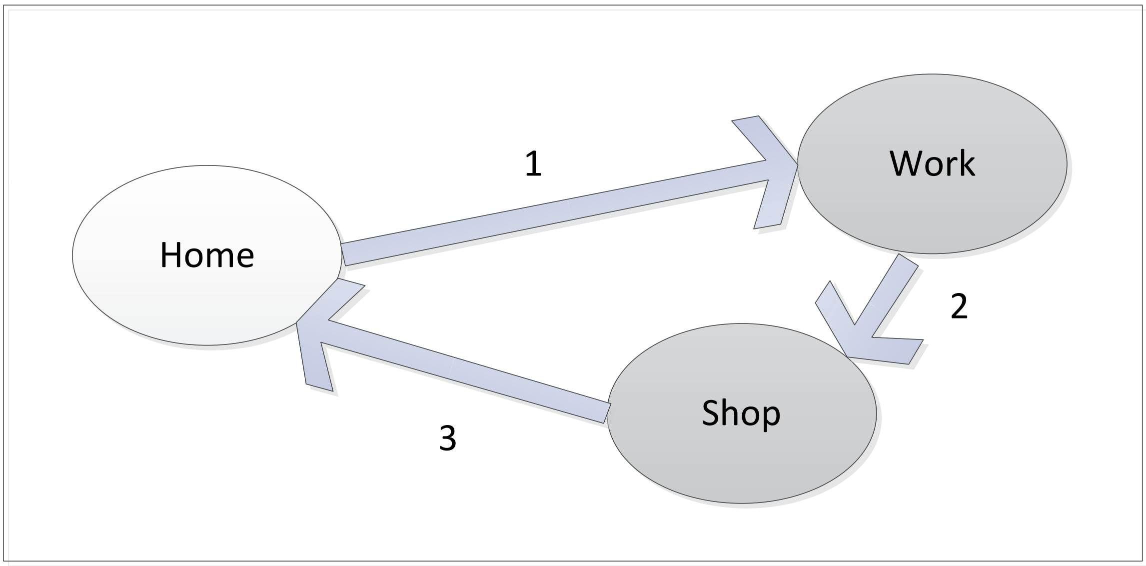
2.1.1. Home-based tours

The key unit of analysis for the mode-destination models is the *home-based tour.* A home-based (HB) tour is a series of linked trips starting and finishing at the traveller's home. The tour-based approach has a number of advantages over traditional trip-based approaches:

- Tour-based approaches model the choice of mode and destination 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, reflecting that 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 usually 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.
- In modelling time period choice, tour-based approaches can explicitly account for the time needed at the destination to carry out the activity appropriate to the trip purpose, e.g. work or shopping. Note, however, that the demand models developed for this project do not model time period choice.
- Non-home-based (NHB) travel is directly linked to the HB travel that occurs as part of the same trip chain in a tour-based approach. By contrast, in a trip-based approach NHB trips typically are forecast independently of HB travel and therefore linkages such as the use of the same travel mode for HB and NHB travel are often lost.

When a traveller makes a direct trip from the home to an out-of-home destination and back again, determining the purpose of the tour is straightforward. However, if two or more out-of-home destinations are visited, it is necessary to define the *primary destination* (PD) in order to determine the main purpose of the tour. This problem is illustrated in Figure 1.

Figure 1. Tour example



In Figure 1, a worker travels directly to work in the morning, but on their way home from work they divert to the shops. In this example either the workplace or shopping destinations could be the PD.

To determine the PD in cases where more than one out-of-home destination is visited, the following purpose hierarchy has been employed:

1. Work
2. Employer's business
3. Education
4. Other purposes.

In the example given in Figure 1, work is higher in the hierarchy than shopping and so the work location forms the PD and work is specified as the purpose of the tour. If there are ties after applying the purpose hierarchy then the destination at which the most time was spent is taken as the PD.[1] If there are still ties after the purpose hierarchy and maximum time criteria have been applied, then of the tied destinations the destination furthest from the home is taken as the PD. If there are still ties after the purpose hierarchy, maximum time and maximum distance criteria are applied, and then the first tied destination visited is taken as the PD (this only happened in a few cases).

[1] For example, in the trip chain home–shopping–shopping–home, both non-home destinations are at level four in the purpose hierarchy and so some further criteria are required to determine which of the two shopping locations that were visited forms the PD.

The trip from the home to the PD is termed the *outward leg* and the trip from the PD back to the home is termed the *return leg*. If both outward and return legs are observed in the data, then the tour is described as a *full tour*. It is assumed in the HB modelling that the traveller makes a direct trip between the home and PD for both tour legs, so that in Figure 1, for example, the detour to the shopping destination is not represented as part of the tour. However, detours are modelled as NHB trips and in the Figure 1 example an NHB detour would represent the additional travel associated with the trip to the shopping destination. It should be noted that 81 per cent of the tours observed in the home interview data involve direct trips to/from the PD – in other words they do not involve any detours.

If only an outward leg or a return leg is observed, then the tour is referred to as an *outward half tour* or a *return half tour*. Some half tours are observed in the data, for example chains of trips that start outside the home and return to home, or chains of trips that leave home but do not return in the 24-hour period in which the survey is undertaken. However, half tours form a low percentage of the data[2] and are therefore not included in the mode-destination models on the basis that higher levels of error are associated with their purpose, mode and other information. To ensure that the total volume of travel predicted by the models is consistent with that observed in the local data, outward half tours *are* included in the frequency models that are documented separately in the frequency report (Jahanshahi et al. 2017).

The process used to identify the samples of HB tours and NHB trips from the local data is termed *tour building*. The tour building analysis is documented in full in Appendix A.

2.1.2. Non-home-based trips

Only NHB trips associated with full HB tours have been used for the development of the NHB mode-destination models.

Linked trips that were made during the course of a HB tour but did not depart from or arrive at home were defined as NHB trips. The travel associated with these trips is modelled within the tour-based approach in two ways:

1. PD-based tours, i.e. a series of linked trips starting and finishing at the same PD, for example if an individual makes a lunchtime trip to the shops (and back to work) during their work day.
2. NHB detours made during the outward or return legs of HB tours, i.e. a single trip to or from the PD, for example if an individual makes a diversion on their trip back home to pick up a child from school.

These two cases are illustrated by the figures below. In Figure 2, trips (2) and (3) form the PD-based tour. In Figure 3, trip (2) forms the NHB detour, and the HB tour is modelled as trip (1) plus a direct movement from work back to the home location (indicated by the dotted line in Figure 3).

[2] Just 2.5 per cent of the tours observed in the home interview data were half tours.

Figure 2. PD-based tour example

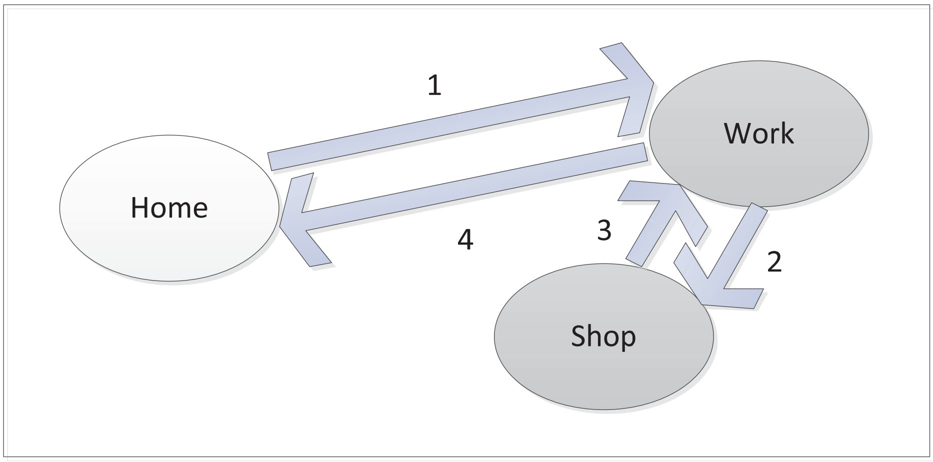
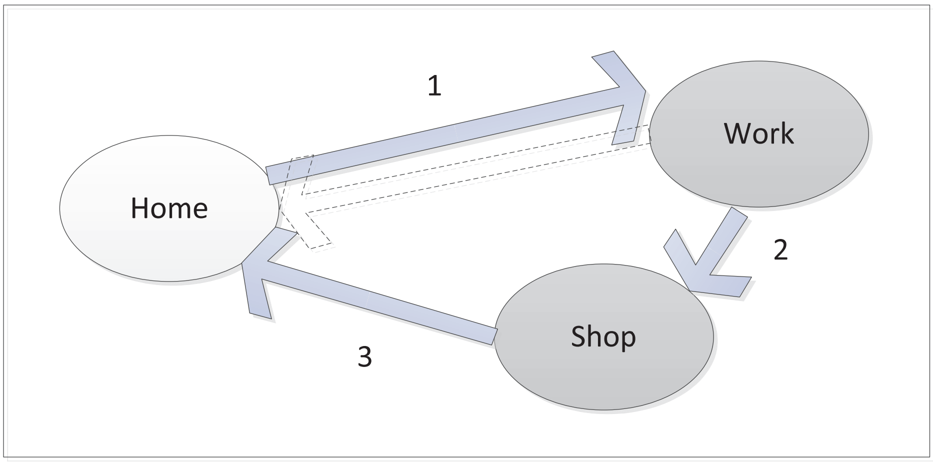


Figure 3. NHB detour example



In the first example, the purpose of the PD-based tours was determined by identifying a *secondary destination* (SD). Most PD-based tours comprised a direct return to the PD, such as PD–EB[3]–PD, for which the SD was readily determined: these are referred to as *simple tours*. However, in some cases chains of three or more trips were observed, such as PD–other–EB–PD. In these cases the SD was identified based on the same rules that have been used for identifying the PD. These are referred to as *complex tours*, and for these tours only direct return travel between the PD and SD is modelled. Separately modelling each of the constituent trips that form complex tours would add significant complexity and is not justified by the low numbers of such tours recorded.

In the second example, the purpose for detours was also determined by identifying the purpose at the SD. Most NHB detours comprised a direct trip to or from the PD, such as home–serve passenger–PD or PD–serve passenger–home, for which the SD was directly determined. In cases where chains of three or more trips were observed, such as home–serve passenger–shop–PD, the SD was identified based on the same

[3] EB denotes Employer's Business.

rules used for identifying the PD, as set out in Section 2.1.1. Thus, similarly to PD-based tours, we have only modelled up to one detour per outbound HB tour leg and up to one detour per return HB tour leg.

Taking the detour example given in Figure 3, the observed trip pattern is home–work–shop–home. The modelling approach represents a direct return tour to the PD, i.e. home–work–home, and the detour from the PD to the SD, i.e. work–shop. The assumption is that on average the distances PD–home and SD–home will be approximately equal and thus modelling work–home rather than shop–home for the return leg gives a reasonable approximation of the actual pattern of travel observed.

2.2. Base year

The base year for the model is 2011. The LTDS choice data was collected over the 2010–2012 period and has been taken to be representative of 2011 travel conditions. The highway, public transport and cycle network information and attraction data supplied as inputs to the mode-destination modelling work are all representative of 2011 travel conditions.

2.3. Purposes

Mode-destination models have been developed for eight different HB purposes:

1. Commute
2. Business
3. Primary education (children aged 5 to 11)
4. Secondary education (children aged 12 to 16)
5. Tertiary education (adults aged 17 and above)
6. Shopping
7. Escort
8. Other travel.

The mapping between the 8 mode-destination purposes and the 14 purpose codes distinguished in the LTDS data is illustrated in Table 1. Note that the allocation of education travel to primary education, secondary education and tertiary education was done by combining purpose code and age information recorded in the LTDS data.

Table 1. Mapping between LTDS purposes and HB tour purposes

LTDS purpose code		HB purpose hierarchy	
1	home	n/a	home
2	usual workplace	1	work
3	delivering/loading	2	employer's business
4	other work	2	employer's business
5	entertainment/sport/social	8	other travel
6	shopping	6	shopping
7	personal business/use services	8	other travel
8	education (as a pupil)	3/4/5	education
9	hotel/holiday home	7	other travel
10	drop off/pick up – work	7	escort other
11	drop off/pick up – school/college	7	escort school
12	drop off/pick up – other	7	escort other
13	worship/other religious observance	8	other travel
14	other	8	other travel
98	missing	-1	missing
99	not asked	n/a	home

For NHB travel the model purposes have been defined based on the interaction between HB and NHB purposes. A total of six NHB purposes have been distinguished, three for PD-based tours and three for detours:

1. Work-related (WR) tours made during WR HB tours: work–work tours for short
2. Non-work-related (NWR) tours made during WR HB tours: work–other tours for short
3. NWR tours made during NWR HB tours: other–other tours for short
4. WR detours made during WR HB tours: work–work detours for short
5. NWR detours made during WR HB tours: work–other detours for short
6. NWR detours made during NWR HB tours: other–other detours for short.

WR HB tours include both home–work (i.e. commute) and home–business. All WR NHB travel is NHB employer's business travel because if the usual workplace is visited during a trip chain it becomes the primary destination due to the HB purpose hierarchy.

2.4. Modes

Seven modes of travel are represented in the NDM mode-destination models:

1. Car driver
2. Car passenger
3. Rail
4. Bus
5. Taxi
6. Cycle

7. Walk.

Rail, also referred to as 'must use rail' in the NDM, has been modelled using a multi-modal PT network including National Rail, London Overground, Tube, DLR and Tram. Bus and walk are available as access and egress modes for 'must use rail' journeys. For rail to be available for a given OD pair at least one of the five rail modes must be used. The bus mode has been modelled using the same PT network but includes journeys made by bus as the only PT mode with access/egress legs undertaken by walk. Section 3.3 discusses this in more detail.

Taxi represents journeys made by both Black Cabs and Private Hire Vehicles.

As discussed in Appendix A, motorcycle tours have been excluded from the mode-destination modelling since they account for just 0.5 per cent of HB tours.

2.5. Times of day

Four time periods have been distinguished in the models:

- AM-peak, 07:01–10:00
- Inter-peak, 10:01–16:00
- PM-peak, 16:01–19:00
- Off-peak, 19:01–07:00.

Tour legs have been classified into time periods based in the mid-point between the tour leg departure and arrival times.

2.6. Zone system

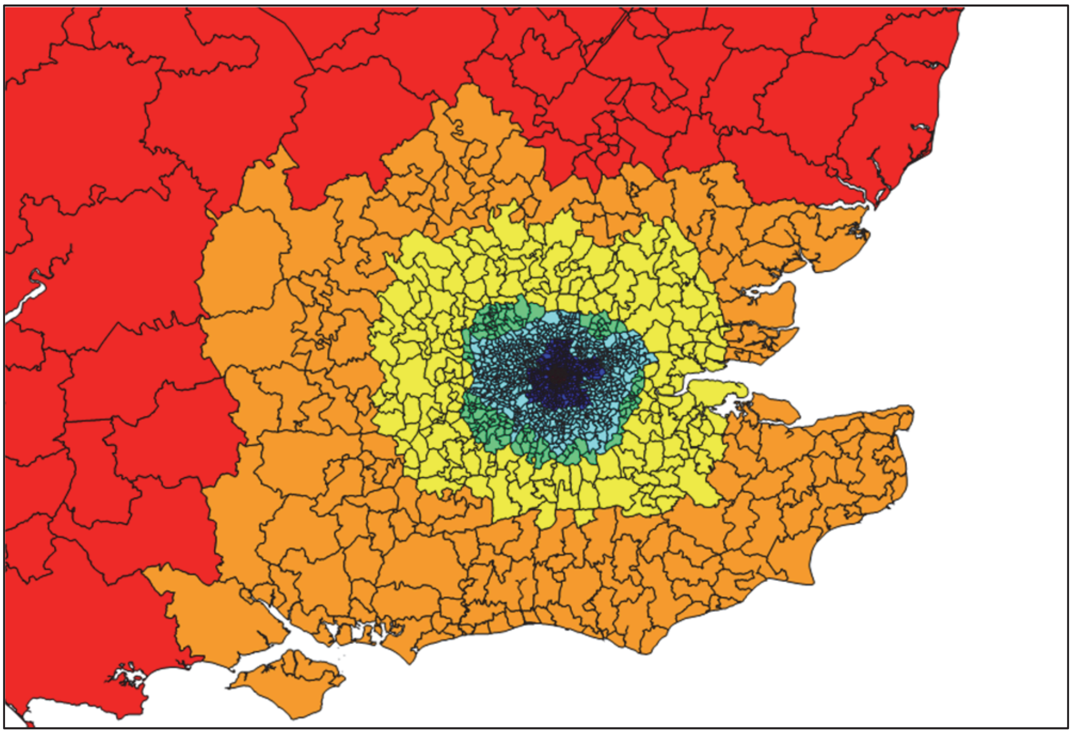
A total of 1,729 zones are represented in the NDM zone system, 1,295 of which cover the study area inside the M25 boundary. Table 2 summarises the number of zones by geographical area.

Table 2. Number of zones by geographical area

Area	Number of zones	Model coverage
Congestion Charging Zone	127	study area
rest of Inner London	438	study area
Outer London	605	study area
annulus	125	study area
collar (approx. 20-km ring around study area)	191	external
rest of South East England	172	external
rest of Great Britain and international	71	external
Total zones	1,729	all of Great Britain

Figure 4 illustrates the model zone system in South East England.

Figure 4. Model zone system in South East England



The study area is shown in Figure 4 in dark blue (Congestion Charge Zone and rest of Inner London), light blue (Outer London) and turquoise (annulus). The external zones are shown in yellow (collar), orange (rest of South East England) and red (rest of Great Britain).

LTDS tour records are observed in the first four area types, which together comprise the study area, and all tours originating in the study area are represented. In the commute model we represent travel from the study area to all destinations in Great Britain. For the other travel purposes we only represent travel originating and ending within the study area. Table 3 summarises the fraction of tours within and outside the annulus.

Table 3. Fraction of tours by geographical area

Home-based purpose	Both origin and destination within annulus	Origins within Outer London but external destinations	Origin in annulus but destinations external	Both origin and destination external
Commute	91.0%	5.5%	0.9%	2.5%
Employer's business	87.5%	8.2%	1.5%	2.8%
Education	93.7%	2.1%	0.9%	3.2%
Shopping	94.4%	2.6%	0.6%	2.4%
Other	92.6%	4.0%	1.0%	2.5%
Escort	93.4%	2.4%	0.6%	3.5%

2.7. Assignment models

TfL assignment models used to produce the LOS data employ more disaggregate zoning systems that are nested inside the NDM zones. These are:

- Railplan, TfL's public transport assignment model. For many years this was implemented using Emme software but it is now implemented in Cube. LTS version 7.1 also makes use of the Cube implementation. Railplan has a detailed network and zoning throughout London and a strategic rail network for the rest of the UK. The latest version has 4,561 zones and the model is calibrated to 2011.
- LoHAM, a London-wide highways assignment model using SATURN software. It is a consolidation of the five regional Highways Assignment Models (HAMs), which are more detailed in North, South, East, West and Central London respectively. Currently there are no versions of LTS that are linked to LoHAM. The latest version of LoHAM has 5,409 zones and is calibrated to a base of November 2012.
- Cynemon is a London-wide cycle assignment model. Cynemon uses the LoHAM zoning system. The Cynemon skims that were supplied for the estimation of the mode-destination models were based on the old LoHAM zoning system that uses 5,194 zones. Going forward, Cynemon and LoHAM will have identical zoning with 5,409 zones represented.

The LOS inputs produced using these three assignment models have been aggregated to the NDM zone system using a demand-weighted averaging approach.

3. Data

3.1. Data on travellers' mode and destination choices

Following discussions with TfL, three years of LTDS data (2010–2012) were used in the tour building process. The LTDS survey collects data by UK financial year (i.e. April to the following March) but since individual interviews are dated it was straightforward to process 2009/10–2012/13 LTDS data to create a 2010–2012 sample.

When processing the 2012 data there was a need to take account of the impact of the 2012 Olympic and Paralympic Games. While LTDS data were collected throughout the period of the games, it would be expected that the travel patterns of Londoners would be impacted both by the games and their associated impact on transport services. Therefore, following TfL's advice, LTDS data from 9 July to 23 September 2012 inclusive have been excluded from the tour building analysis.

Only weekday records were retained in the tour building, as travel patterns would be expected to be significantly different at weekends and are not currently within the scope of the LTS model. However, the LTDS data used in the model development work were collected throughout the year and therefore include both school holiday periods and bank holidays. Thus the mode-destination models that have been developed represent an average weekday. For information on the LTDS sample sizes please refer to Appendix A.

3.2. Highway level-of-service data

Highway LOS was derived from TfL's London Highway Assignment Model (LoHAM). LoHAM is built up from five separate SATURN models covering Central London (CLoHAM), South London (SolHAM), West London (WeLHAM), North London (NoLAM) and East London (ELHAM).

LoHAM has been calibrated to a base of November 2012. The NDM works with a 2011 base year and it has been assumed that the LoHAM November 2012 assignments can be taken to be representative of 2011 travel conditions.

Three time periods are distinguished in LoHAM:

- AM peak, 08:00–09:00
- Inter-peak, 10:00–16:00 (average hour)
- PM-peak, 17:00–18:00.

The peak-periods assignments are for one hour of each peak period, 08:01–09:00 for the AM-peak and 17:01–18:00 for the PM peak. The LOS for the rest of the peak periods[4] has been calculated as the average of the peak-hour LOS and the inter-peak LOS. In the absence of an off-peak assignment the inter-peak LOS has been used to represent off-peak travel conditions. This approach assumes that the routing and levels of congestion observed in the inter-peak period can be taken as representative of off-peak conditions. In reality we would expect lower congestion in the off-peak period and so some journey times would be expected to be lower than in the inter-peak. As the proportion of journeys undertaken in the off-peak period is relatively small, the described limitations are not expected to have a material impact on the overall quality of the model estimation.

For each of these three time periods the following LOS components were supplied for each origin-destination (OD) pair:

- Distance (km)
- Travel time (minutes)
- Congestion Charge toll indicator
- Dartford Crossing Charge indicator.

The LOS from the detailed zoning system used in LoHAM, with 5,409 zones, was converted to the 1,729-zone system used for the mode-destination models.

The LoHAM distance and time skims do not include distance and travel times to zone centroids and so these have been added (in ALOGIT[5]) before the information enters the model utilities. Appendix C shows the highway LOS information for a few example OD pairs.

LOS has been generated for intrazonals (i.e. movements with the same origin and destination zone) by identifying the nearest zone (by distance) and then halving the distance and travel time to that zone. The same approach will be followed in model implementation.

The OD distances and travel times were used to calculate speeds per OD pair, and from these per-kilometre car costs have been calculated (for each OD pair) using the quadratic functions set out in the Department for Transport's TAG databook (Version 1-5, Summer 2016). Separate functions have been applied for work (i.e. business) and non-work (all other purposes) travel.

The Congestion Charge cost was applied if the LOS skims indicated that the Congestion Charge Zone was entered for *either* the outward or return tour leg. It was assumed that travellers paid using the auto pay option, which in 2011 meant a charge of £9. For residents of the Congestion Charge Zone the 90 per cent residents discount was applied. Note that for PD-based tours, the Congestion Charge is not applied when the associated HB tour has already paid the Congestion Charge, to avoid double-counting.

For the Dartford Crossing the charge per crossing of £1.50 that was levied in 2011 was applied for those OD pairs indicated by the skims to have used the crossing. Unlike the Congestion Charge, the Dartford Crossing Charge is levied in both tour directions if both movements use the crossing.

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[4] 07:01–08:00 and 09:01–10:00 for the AM peak; 16:01–17:00 and 18:01–19:00 for the PM peak.

[5] For more information on the ALOGIT model estimation software used for this work, see: http://www.alogit.com/

The same Congestion Charge and Dartford Crossing costs have been assumed in model implementation for the base year.

Hourly parking costs were applied as a function of the length of stay at the primary destination. For tours travelling out in the AM-peak period, peak-period parking costs were applied; for tours travelling out in all other time periods, inter-peak parking costs were applied.

3.2.1. Taxi fares

Distance-based costs of 282 p/km for black cabs and 155 p/km for private hire vehicles were provided by TfL. These are 2015 prices and so have been deflated to 2011 prices for the models. Weighted average costs per kilometre were calculated based on varying splits of black cab usage by journey origin zone (based on analysis of LTDS data):

- 80 per cent for Central London origins
- 47 per cent for Inner London origins
- 14 per cent for Outer London
- 23 per cent for annulus zones.

The weighted average kilometre costs were then multiplied by the highway distance skim for the OD pair to calculate the taxi cost for the OD pair.

3.3. Public transport level-of-service data

PT LOS data were supplied by TfL's Railplan model, which uses Cube software. The LOS from the detailed zoning system used in Railplan, with 4,561 zones, was converted to the 1,729-zone system used for the mode-destination models.

As per the highway LOS, the PT LOS only distinguishes AM-peak, inter-peak and PM-peak periods. In the absence of an off-peak model, it was agreed with TfL that off-peak LOS should be taken from the inter-peak period, with the assumption that the same services are operated in both directions and at all times. In reality we would expect different service provision in the off-peak period, which could result in longer or shorter journey times depending on the location. As the proportion of journeys undertaken in the off-peak period is relatively small, the described limitations are not expected to have a material impact on the overall quality of the model estimation.

The PT model represents time periods as opposed to peak hours. Therefore, no peak averaging was undertaken for the PT LOS.As the zone sizes in the study area are relatively small, the rail and bus PT modes have been set to be unavailable for intrazonal tours.[6]

[6] The home–other model was investigated to test the impact of setting intrazonals to be unavailable for PT tours. No train tours and just a single bus tour were dropped from the model as a result of this condition.

3.3.1. Rail skims

Rail skims were generated both for travel within Greater London and for travel from Greater London to nationwide destinations.

In the rail skims all of the PT modes represented in Railplan are available when the LOS is skimmed from the PT network:

- National Rail/London Overground
- Tube
- DLR
- Tram
- Bus.

For a given OD pair, the Cube skimming process determines which of these five modes is used and it is possible for combinations of the PT modes to be used for a given OD movement. The skimming process used weights of 1 for in-vehicle time, 2 for walk times and 2.5 for most wait times, but with lower values where trains split/join en route.

The following rail components were supplied:

- National Rail/London Overground in-vehicle time (minutes)
- Tube in-vehicle time (minutes)
- DLR in-vehicle time (minutes)
- Tram in-vehicle time (minutes)
- Bus in-vehicle time (minutes)
- First wait time (minutes)
- Interchange wait time (minutes)
- Access time (minutes)
- Egress time (minutes)
- Interchange walk time (minutes)
- Crowded time (minutes)
- Boardings
- Fare (pence).

Appendix C shows the rail LOS information for a few example OD pairs.

In the demand modelling, the rail mode is only represented as available if there is travel time on at least one of the following four rail modes: National Rail/London Overground, Tube, DLR and Tram. If the only PT mode with non-zero travel time is bus, then rail was set to be unavailable for the OD pair. For short journeys it is possible that the skim process identified walking all the way between the origin and destination to be the best path through the network; in these instances rail was set to be unavailable in the models.

3.3.2. Bus skims

The Railplan model only codes for TfL operated bus services. Some of these extend beyond the Greater London area boundary.

To generate the bus skims, the only PT mode available in the Railplan PT model is bus. The following components were provided:

- Bus in-vehicle time (minutes)
- First wait time (minutes)
- Interchange wait time (minutes)
- Access time (minutes)
- Egress time (minutes)
- Interchange walk time (minutes)
- Crowding time (minutes)
- Boardings
- Fare (pence).

Appendix C shows the bus LOS information for a few example OD pairs.

For short journeys it is possible that the skim process identified walking all the way between the origin and destination as the best path through the network; in these instances bus was set to be unavailable in the models.

3.3.3. Treatment of fares

The fare data reflect full single fares without any concessionary fare discounts applied. For commute and employer's business travel, uniform discount factors taken from the previous strategic model for London, LTSv7.1, were applied to take account of some use of concessionary fares.

Table 4. Concessionary fare discount factors, commute and employer's business travel

Purpose	Discount factor
Commute, white collar occupations	0.97
Commute, blue collar occupations	0.95
Employer's business	0.91

Source: LTSv7.1 model.

It can be seen that the level of discounting is low for commute and employer's business travel, with discount factors close to one (i.e. no discount).

For all other purposes, where higher discounts are expected, age and working status information has been used to identify the discount. Using information from the TfL website,[7] the following discounts have been applied to the fares as a function of the age and working status of the individual:

- Children aged under 11 travel for free on rail and bus services.
- Children aged 11 to 18 travel for free on bus services and at a 50 per cent discount on rail services.
- Students aged 18 and above pay 70 per cent of the full fare for rail and bus services.
- Individuals aged 60 and above are eligible for Freedom Passes, which offer free bus and tube travel, and free National Rail travel after 09:30.

As it is not possible to split the fare between tube and National Rail travel components, it has been assumed that Freedom Pass holders pay zero rail fares for travel at all times of the day. This assumes that anyone travelling before 09:30 who is eligible for a Freedom Pass travels by tube rather than National Rail if they choose the rail mode.

3.4. Attraction data

The following attraction data were supplied by the project team for use in the mode-destination modelling:

- Population
- Total employment
- Retail employment
- Service employment
- Primary school enrolments
- Secondary school enrolments
- Tertiary education enrolments
- Retail floor space.

Section 4.2 discusses how this information has been used to specify the attractiveness of competing destination zones in the modelling.

[7] https://tfl.gov.uk/fares-and-payments/travel-for-under-18s/travelling-with-children; https://tfl.gov.uk/fares-and-payments/adult-discounts-and-concessions/freedom-pass (accessed 18/05/17).

4. Nested logit model specification

4.1. Mode and destination alternatives

Up to seven modes are represented in the models:

1. Car driver
2. Car passenger
3. Rail
4. Bus
5. Taxi
6. Cycle
7. Walk.

Note that car driver is not available in the home–primary and home–secondary education models as individuals aged under 17 cannot drive.[8] All seven modes are represented in the models for the remaining HB and NHB travel purposes.

The destination alternatives in the model are the 1,729 zones that cover the study area and the rest of GB. However, only in the commute model are zones in both the internal and external areas available. For other model purposes, which were developed after commute, it was decided to restrict destination availability so that the models only represent travel to the 1,295 internal destination zones.[9] External destinations were dropped because better-quality models were obtained when they were excluded, and in particular dropping them helped to increase cost sensitivity in the models. The full choice between internal and external destinations will be represented in the model implementation.

The mode-destination alternatives are represented as available in the models if the following conditions are met:

- For all modes a non-zero attraction variable must be defined for the destination zone for it to be available in the choice set.
- For purposes other than commute the destination zone must lie in the internal area.

[8] All education travel made by individuals aged 17 and above is classified as tertiary education.

[9] Restricting destination availability in this way resulted in the omission of substantial number of tours. For home–business 320 tours were dropped, for home–shopping 259 were dropped and for home–other 435 tours were dropped.

- Car driver is available if the traveller holds a driving licence and if there is at least one car in the household.
- Car passenger is available to all travellers. It is assumed that persons in households without a car can still travel as a car passenger with a person from outside their household.
- Rail is available to travellers if a train service exists for their journey, i.e. the rail LOS gives a non-zero rail IVT for both the outward and return legs of the tour. No rail LOS exists for intrazonals and therefore these are set to be unavailable.
- Bus is available to travellers if a bus service exists for their journey, i.e. the bus-only LOS gives a non-zero bus IVT for both the outward and return legs of the tour. Bus LOS is not defined for the external area and therefore bus is unavailable for travel to external destinations. No bus LOS exists for intrazonals and therefore these are set to be unavailable.
- Taxi is available to all travellers.
- Cycle is available to all travellers travelling to destinations in the study area. For commute, cycle is set to be unavailable for travel to external zones.
- Walk is available to all travellers travelling to destinations in the study area. For commute, walk is set to be unavailable for travel to external zones.

4.2. Attraction variables

Attraction variables are used to capture the relative attractiveness of competing destination alternatives. The models are formulated such that the attraction variables enter the utility functions as 'size' terms. The practical implication of the size term formulation, whereby the attraction term is logged before it enters the utility function, is that the number of tours predicted to travel to each zone is directly proportional to the attraction variable, all else being equal.

The size variables tested for each purpose are based on RAND Europe's experience from developing other model systems, in particular the PRISM West Midlands and Sydney model systems.

Table 5. Attraction variables tested by purpose

Purpose	Attractions
commuting	total employment
home–business	total employment
home–primary education	primary education enrolments
home–secondary education	secondary education enrolments
home–tertiary education	1) university enrolments 2) education employment
home–shopping	retail employment retail floorspace service employment
home–escort	population total employment primary education enrolments secondary education enrolments
home–other travel	population service employment retail employment
work–work tours	total employment
work–other tours	population service employment retail employment
other–other tours	population service employment retail employment
work–work detours	total employment
work–other detours	population total employment retail employment
other–other detours	population service employment retail employment

For purposes where more than one attraction (or size) variable is used, a base size variable is specified and then the relative importance of the other attraction variables relative to the base size variable is estimated from the data. In each purpose where multiple size variables have been used except home–shopping, population is used as the base size variable and then the importance of the other size terms is estimated relative to population.

For home–tertiary education, the initial model tests were undertaken using university enrolments. However, significant numbers of observations were excluded from the model because they were observed to travel to destination zones with zero enrolment data. Therefore, total education employment was tested instead, and this overcame the loss of data problem. Ideally tertiary education enrolments rather than total education employment would be used to give more realistic distribution patterns and this is a potential improvement to the models in any future estimation work.

4.3. Treatment of monetary cost sensitivity

4.3.1. Cost damping

In contrast to many UK transport models, the mode-destination models do not take values of time (VoTs) as fixed inputs. Instead, separate sensitivity parameters have been estimated for both monetary cost and IVT and other LOS components. This approach allows local cost sensitivity parameters to be estimated that give the best possible explanation of the local choices, in this instance the mode-destination choices observed in the LTDS data.

The cost formulations used in the mode-destination models incorporate cost damping – where the marginal impact of cost on utility reduces with increasing cost – using formulations consistent with the guidance set out in Section 3.3 of WebTAG Unit 3.3 (Department for Transport 2016). The starting point in the model specification searches was to estimate models with separate linear cost and log cost terms. This formation has been found to give more plausible fuel cost elasticities and an enhanced fit to the data than linear cost only, or log cost only, formulations (Fox et al. 2009).

For some model purposes, it was not possible to estimate statistically significant and correctly signed linear and log cost terms reflecting increasing disutility with increasing cost. For these purposes, a 'gamma formulation' has been adopted whereby a linear-log cost mixture is imposed and a single cost sensitivity parameter is estimated. Equation (4.1) shows the formulation that has been adopted:

$$\beta_{GammaCost}\left\{\gamma.\text{cost}+\left(1-\gamma\right)\log(\text{cost}).\frac{\text{E(cost)}}{\text{E(log(cost))}}\right\} \tag{4.1}$$

where: $\beta_{GammaCost}$ is the estimated sensitivity to the gamma cost term

γ controls the relative contribution of linear and logarithmic cost

E(cost) is the mean cost

E(log(cost)) is the mean logarithmic cost

the ratio *E(cost) / E(log(cost))* ensures linear and logarithmic cost use the same scale

Gamma takes values ranging from 0 to 1, and it can be seen that at a value of 0 the term in brackets is a pure log-cost form whereas at a value of 1 the term in brackets is a pure linear-cost form. The cost specification searches tested different gamma values and investigated the impact on fit to the observed LTDS choices, the implied VoTs and the realism test results, and in particular the impact on the car fuel cost kilometrage elasticities.

4.3.2. Cost sharing between car drivers and passengers

Cost sharing is represented in the models so that the predicted levels of demand for car driver and car passenger are sensitive to car cost changes.

The cost sharing is implemented by specifying cost components for the car driver and car passenger utility functions as specified in Equations (4.2) and (4.3):

$$V(Cost)_{CD} = \beta_{Cost} CarCost_{OD} \left[1 - \frac{S(O_{CD} - 1)}{O_{CD}} \right] \tag{4.2}$$

$$V(Cost)_{CP} = \beta_{Cost} CarCost_{OD} \left(\frac{S}{O_{CP}} \right) \tag{4.3}$$

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 LTDS data (by purpose)

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

If S takes a value of 0, there is no cost sharing and the driver pays the full cost. If S takes the value of 1, there is equal sharing, with drivers and passengers paying an equal share. Intermediate values of S imply that both drivers and passengers contribute towards the total cost, but that the driver pays a greater share. The value of S that gives the best fit to the observed data is determined by testing different S values iteratively.

Mean occupancies[10] were used rather than observed occupancies because while the latter can be calculated for individuals who choose car driver or car passenger, occupancy information is not available for individuals who choose PT, cycle, walk or taxi modes. The observed mean occupancy values by purpose are presented in Table 6. Note that values are only presented in Table 6 for those purposes where car cost sharing has been implemented.

Table 6. Mean occupancy values

Purpose	Car driver	Car passenger
commuting	1.141	2.180
home–tertiary education	1.216	2.728
home–shopping	1.404	2.368
home–other travel	1.366	2.598

Source: Analysis of 2010–2012 LTDS data.

Car driver is not represented in the primary and secondary education models and so no cost sharing tests have been made in those cases.

For business travel, it is also assumed that it is the driver, rather than any passengers, who bears all of the car costs. This is because car costs can be reclaimed from an individual's employer and it is assumed that

[10] The mean occupancy value is calculated by identifying the total number of shared car trips from the tours generated from the same household. We assume that a trip is shared if the driver and the passenger depart at the same time.

this is done by the driver. Therefore cost sharing between drivers and passengers was not modelled for the three business purposes (home–business, WR tours made during WR HB tours, and WR detours made during WR HB tours).

The majority of escort travel is escorting children to education or other activities after school, and furthermore the car passenger mode share is very low (2.75 per cent). Therefore in the home–escort model it has been assumed that the driver (normally the parent of an escorted child) bears the cost of the travel and therefore all car costs are represented on the car driver utility.

For the four non-business NHB purposes (NWR tours made during WR HB tours, NWR tours made during NWR HB tours, NWR detours made during WR HB tours and NWR detours made during NWR HB tours), mean home–other travel occupancies have been used because the home–other estimation sample has far more car driver and car passenger observations than the NHB purposes, allowing more reliable mean occupancy values to be calculated.

4.3.3. Interaction with income

Variation in cost sensitivity with personal income band was investigated during the model specification search. For models with separate linear cost and log cost terms, separate linear cost parameters were estimated for each income band. For models with a gamma cost formulation, the income interaction was applied to the gamma cost parameters.

Initially in the specification search a model was estimated with ten income-segmented cost sensitivity terms, one for each of the ten gross household income bands recorded in the LTDS data:

1. Less than £5,000 p.a.
2. £5,000 to £9,999 p.a.
3. £10,000 to £14,999 p.a.
4. £15,000 to £19,999 p.a.
5. £20,000 to £24,999 p.a.
6. £25,000 to £34,999 p.a.
7. £35,000 to £49,999 p.a.
8. £50,000 to £74,999 p.a.
9. £75,000 to £99,999 p.a.
10. £100,000 or more.

The significance levels of each of the ten cost terms were then calculated and the cost parameters were merged where the estimates for neighbouring bands were not significantly different from one another. This process was repeated until an income segmentation was identified where cost sensitivity decreased with increasing income and where each cost sensitivity parameter was statistically different from its immediate neighbours.

4.4. Level-of-service terms

The starting point for the LOS specification searches was to estimate separate model parameters for each LOS component and separate linear and log cost parameters for monetary cost components. Table 7 summarises the LOS components that were incorporated in the utilities of each of the seven modelled modes.

Table 7. LOS model specification

Component	Car driver	Car pass.	Rail	Bus	Cycle	Walk	Taxi
driving cost	cost	cost					cost
toll cost	cost	cost					cost
parking cost	cost	cost					
train fare[11]			cost				
bus fare				cost			
total car time	CarTime	CarTime					TaxiTime
parking search time	PrKgTm	PrKgTm					
rail time			TrainTime				
bus time			BusTime	BusTime			
access/egress time			AcEgTime	AcEgTime			
interchange walk time			AcEgTime	AcEgTime			
initial wait time			WaitTime	WaitTime			
other wait time			WaitTime	WaitTime			
boardings			Boardings	Boardings			
crowding time			CwdTm	CwdTm			
distance		CarPDist				WalkDist	
generalised cycle distance					CycleDist		

It can be seen from Table 7 that interchange walk time is represented together with access and egress time in a combined access and egress walk term that covers walk access time to the first PT service, any walk time incurred while interchanging between PT services, and walk egress time onwards to the final destination.

Car passenger, car driver, cycle, walk and taxi modes are modelled as being 'available' for intrazonal movements. The intrazonal LOS that is supplied for these modes is generated by assuming half the LOS to the nearest neighbouring zone and so represents an approximation of the actual intrazonal LOS. For this reason intrazonal constants have been tested in the model estimation process to capture any additional intrazonal effects. As noted in Chapter 3, PT modes are unavailable for intrazonal movements.

The treatment of cycling and walking LOS is discussed in more detail in the following section.

[11] Including any bus fare payable for the route.

4.5. Representation of cycling and walking

Analysis was undertaken by the project team to quantify how propensity to cycle varied between individuals in the LTDS data. The analysis looked at how cycle mode share varied across eight explanatory variables:

- Gender
- Borough of residence
- Household car ownership
- Ethnic group
- Age
- Adult status
- Whether the individual has long-term health problem/disability that limits daily activity
- Household income.

A logistic regression model was estimated to predict an individual's propensity to cycle as a function of these eight variables. Individuals were then classified into either low cycle propensity (LCP) or high cycle propensity (HCP) groups based on the propensity to cycle scores from the logistic regression.

The mode-destination model estimation work then investigated whether the HCP group had a significantly higher likelihood of travelling by cycle, tested using an HCP mode constant, and whether they were less sensitive per minute of generalised cycle time, tested using an HCP generalised cycle distance term.

The generalised cycle distance measure used for this work was taken from TfL's Cynemon model, which represents the London cycle network. The generalised cycle distance measures take account of the level of hilliness in the skimmed routes.

Walking distance information was produced using information taken from the Cynemon model. The Cynemon LOS data will also be used in the model implementation.

4.6. Segmentation terms

The segmentation terms tested in the model were informed primarily by the segmentation task, led by Mott MacDonald. This led to a shortlist of candidate segmentation variables to be tested in the mode-destination modelling:

- TfL Classification of Londoners (TCoL) (new geo-demographic segmentation)[12]
- Household income
- Household composition (number of adults and children)
- Household car ownership (number of cars)
- Household driving licence holders (number of people with licence)
- Population density

[12] This is a geo-demographic segmentation that has been developed for TfL to help explain variation in travel patterns across London.

- Socio-economic classification/employment status
- Industry of employment
- Car availability
- Gender
- Age
- Disability
- Freedom pass ownership
- Propensity to cycle.

Drawing on RAND Europe's experience from other model studies, the household licence holding and car ownership segmentations were combined to form car availability segmentations. The following segmentations have been found to help explain the choice of car driver and car passenger modes:

1. Zero cars
2. No individual licence, but car in the household
3. Licence, one car, car competition – more licence holders than cars
4. Licence, one car, free car use – licence holders less than or equal to number of cars
5. Licence, two-plus cars, car competition – more licence holders than cars
6. Licence, two-plus cars, free car use – licence holders less than or equal to number of cars.

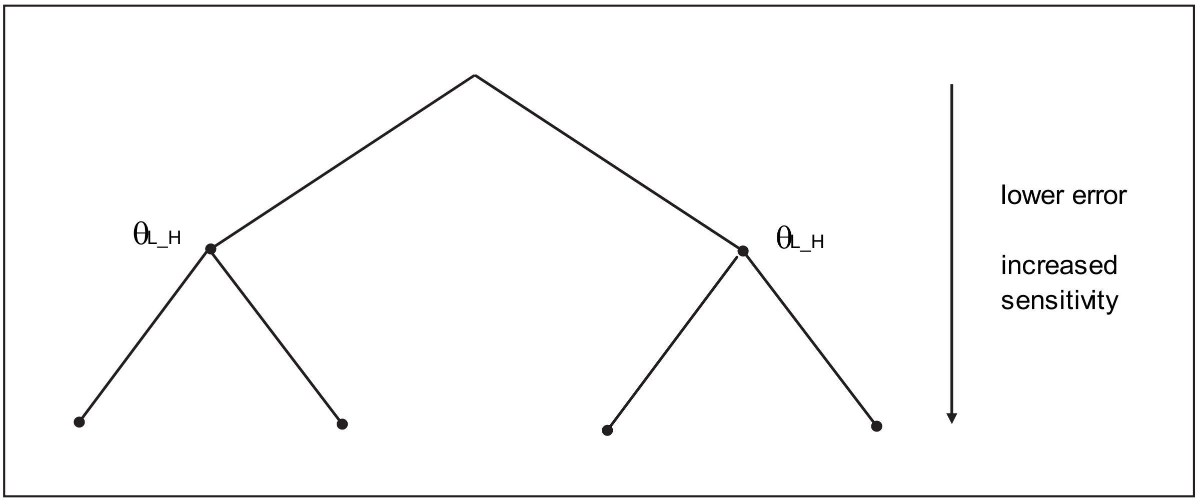
The car driver alternative is only available for segments 3 to 6, and is more likely to be chosen in segments 4 and 6 than 3 and 5 because there is no competition for cars in the household. It is assumed that all people can travel as a car passenger, as it is possible to accept a lift from someone outside the household, but car passenger is much more likely to be chosen for segments 2 to 6 where there is a chance that another household member can offer a lift. To account for this effect, a passenger opportunity term is applied to the car passenger utility for households that own cars where at least one other person in the household owns a licence and so could offer the individual a lift.

4.7. Structural tests

Initial models were developed using multinomial specifications where mode and destination choices have equal sensitivity to changes in utility. Once the final model specifications had been identified, structural tests were carried out to explore the relative sensitivities of the different responses.

To perform the structural tests, nested logit structures were set up with the different choices represented at different levels in the structure, as illustrated in Figure 5.

Figure 5. Nested structures



Choices lower down in the structure have lower levels of error, and are more sensitive to changes in utility. Less error means that the unobserved component of utility is lower relative to the observed component of utility, and therefore the observed component of utility is better able to explain the observed choices. 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, i.e.:

$$\theta_{L\_H} = \frac{\sigma_L}{\sigma_H} \qquad (4.4)$$

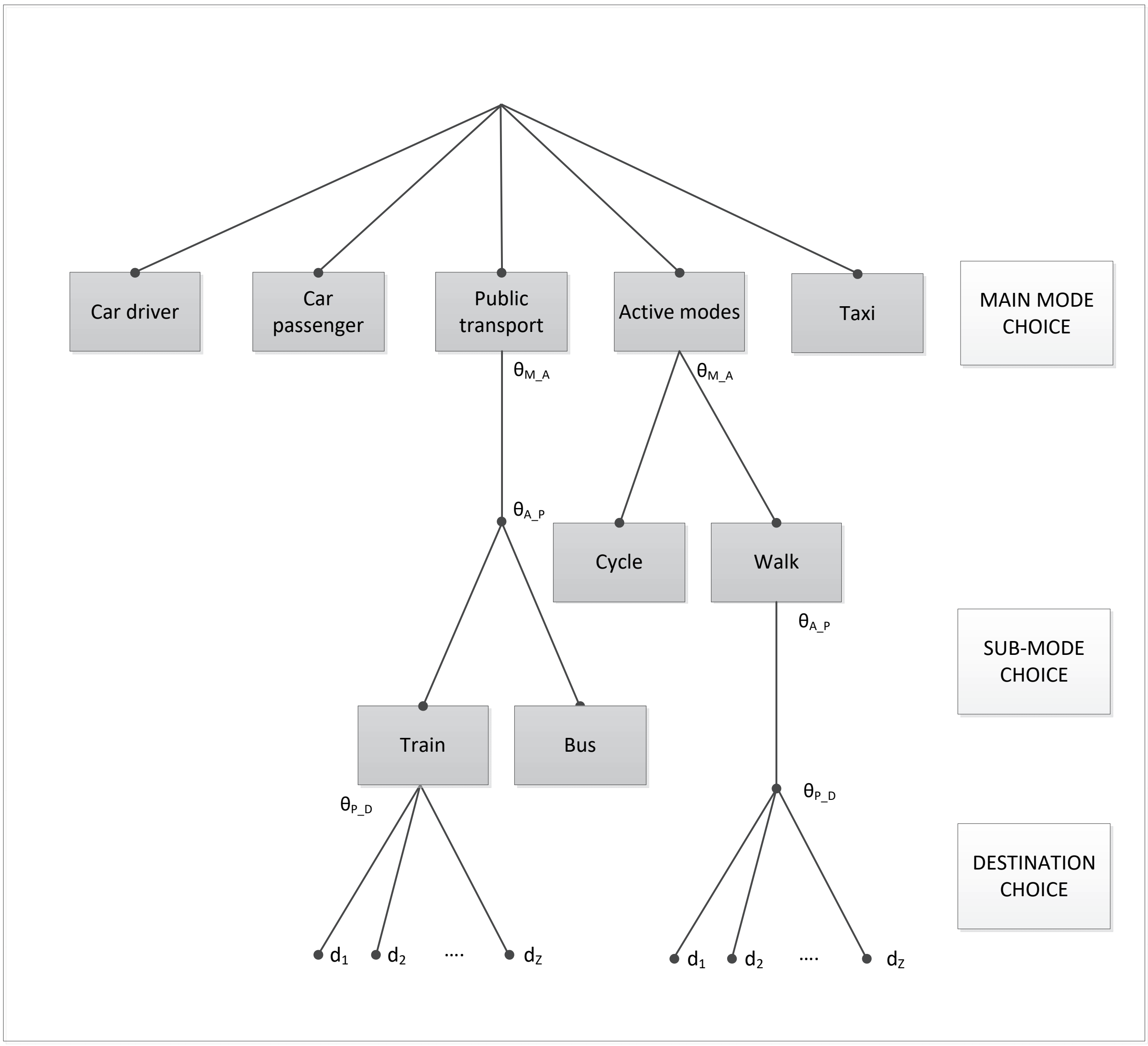
where: σ_L is the standard deviation of the error in the utilities at the lower level

σ_H is the standard deviation of the error 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 $0 < \theta_{L\_H} \leq 1$. If a model was estimated that gave $\theta_{L\_H} > 1$ then the structure was rejected and a structure was tested with the higher and lower levels reversed or the parameter would be constrained to a value of one.

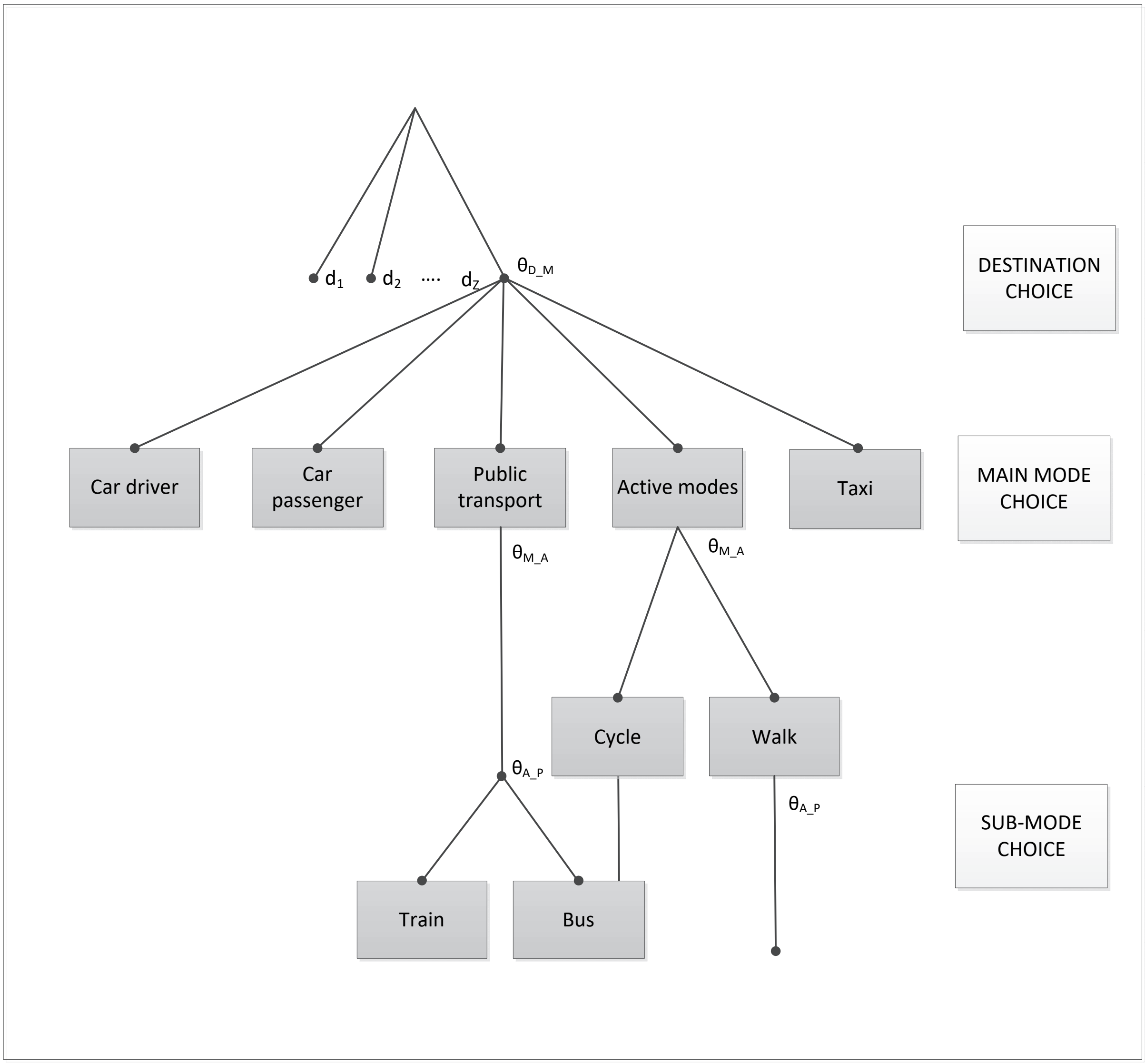
Two model structures have been tested. In the first structure, mode choice lies above destination choice and two sub-nests for active (cycle and walk) and PT (rail and bus) modes are tested. This structure is consistent with WebTAG Unit M2 guidance in that mode choice is above (less sensitive than) destination choice. In the second structure, destination choice lies above mode choice and sub-mode nests are also included for active and PT modes. The nesting structures tested are illustrated in Figure 6 and Figure 7. It is noted that the tree structures incorporate scaling so that the utilities are in the same units for each branch, which is necessary when setting up nesting structures with ALOGIT.

Figure 6. Modes above active modes above PT modes above destinations structure



The theta values show the structural parameters that have been estimated to determine the relative sensitivity of adjacent choices in the structure. The nesting parameter names use the following abbreviations: M for main modes, A for active modes, P for public transport modes and D for destinations.

Figure 7. Destinations above modes above active modes above PT modes structure



5. Nested logit model results

5.1. Cost specification

5.1.1. Cost formulation

Home-based models

For the commute model, it was possible to estimate separate linear cost and log cost terms that were plausible (negative) and implied sensible values of time by mode. The linear cost terms were interacted with household income. Three income bands were found to give significant variation in cost sensitivity with income:

- Gross household income less than £35k per annum
- Gross household income £35–75k per annum
- Gross household income over £75k per annum.

The relatively high breakpoints between the three bands may reflect the fact that commuters' incomes in London are significantly higher than average.

Given that the commute model specification differs from most UK transport models, which work with a generalised cost formulation, we have created a test whereby the final commute specification is modified to use a generalised cost formulation. The following tables summarise the impact on model fit and on the key IVT sensitivities.

Table 8. Impact on model fit of using a generalised cost formulation for commute

	Linear and log cost specification	Generalised cost formulation
Observations	8,365	8,365
Log-likelihood	-54,045.1	-54,118.8
Degrees of freedom	49	46

The loss of log-likelihood of 73.7 points for three degrees of freedom is significant at a 95 per cent confidence level, i.e. the linear and log cost specification gives a significantly better model than the generalised cost formulation.

Table 9. Impact on level-of-service terms of using a generalised cost formulation for commute

	Linear and log cost specification		Generalised cost formulation	
Car time	Car time	-0.0339 (33.5)	Generalised car time	-0.0317 (73.3)
Rail time	Rail time	-0.0118 (11.7)	Generalised rail time	-0.0139 (22.9)
Bus time	Bus time	-0.0275 (32.2)	Generalised bus time	-0.0281 (35.9)

Moving to a generalised cost formulation leads to some reduction in the car time estimate, and an increase in the rail and bus time estimates. However, none of the changes is particularly large.

For the home-business model, when separate linear cost and log cost parameters were tested the linear cost parameter was positive and therefore a gamma cost formulation was adopted using a gamma value of 0.01. The low value for gamma was selected because with higher gamma values the implied values of time were too high and the model fit deteriorated. Variation in sensitivity to cost was identified using two income bands:

- Gross household income less than £50k per annum
- Gross household income over £50k per annum.

No costs are represented in the home–primary and home–secondary education models, since car driver is not modelled and school children are eligible for free bus and rail travel.

For the home–tertiary education model, linear and log cost parameters have been estimated. We could not identify any segmentation of these cost parameters by income band.

For the home–shopping, home–escort and home–other travel models, it was not possible to estimate linear and logarithmic terms or models using a gamma cost specification that gave rise to plausible values of time (VoTs). In particular, the cost parameters were weakly estimated leading to implausibly high VoTs. Given these differences, cost sensitivity information was imported from the commute model. Cost sensitivity was adjusted for VoT differences between commute and other travel using guidance on VoTs from WebTAG, and adjustments were also made for differences in the overall model scale through the car time parameter. The transformed cost was then added, expressed in car time units (for all motorised modes). This approach ensured that plausible VoTs and variation in sensitivity to cost with income and trip length were represented for discretionary travel purposes (although these were determined from the commute model).

Equation (5.1) demonstrates how the commute cost formulation was transferred to the discretionary travel purposes. It shows how the cost contributions for **all modes with a monetary cost** represented have been added to the utility functions in car time units for models where we could not identify sensible cost parameters (note, therefore, that this includes public transport modes and taxi as well as car driver and passenger):

$$\beta_{CarTime}\left(\frac{VOT^{C}}{\beta^{C}_{CarTime}*VOT^{O}}\left[\beta^{I,C}_{cost}cost+\beta^{I,C}_{Logcost}*\ln(cost)\right]\right) \qquad (5.1)$$

where: $\beta_{CarTime}$ is the estimated car time parameter for the purpose

$\beta^{C}_{CarTime}$ is the car time parameter in the commute model

VOT^{C} is the WebTAG VoT for commute (£10.22 per hour in 2011 prices and values)

VOT^{O} is the WebTAG VoT for other travel (£4.67 per hour in 2011 prices and values)

$\beta^{I,C}_{cost}$ is the linear cost parameter for income band *I* in the commute model

$\beta^{I,C}_{LogCost}$ is the log cost parameter for income band *I* in the commute model

cost is the cost of travel for the OD pair for the mode in question

Non-home-based models

For all of the NHB models except the work–work detour model, we were not able to estimate VoTs and therefore these were imported from WebTAG using the distance function given in the WebTAG databook (Department for Transport Spring 2016 release, Version 1.5). For purposes other than business, WebTAG assumes that VoTs are uniform across modes. These VoTs were used to convert costs into time units, and then sensitivities to generalised time were estimated separately by mode.

For work–work tours the WebTAG distance function for car travel in work time was used. A separate rail function is also presented but for modelling purposes a single VoT was required that can be applied across all modes with monetary cost components – i.e. car, rail, bus and taxi – and therefore the car VoT formulation was selected. The car cost function that was used is detailed in Equation (5.2), which is taken from Table A1.3.1 of the WebTAG databook.

$$VOT=\frac{U}{\left(1+e^{\frac{x_{mid}-D}{k}}\right)} \qquad (5.2)$$

where: U is £29.52 (market prices)

x_{mid} is 66.53

D is the distance in km

k is 67.02

For the non-work purposes, using distance-varying VoTs was found to give a better fit to the data than using fixed VoTs. The distance-varying VoT formulation was taken from WebTAG Unit M2:

$$VOT_d = VOT\left(\frac{d}{d_0}\right)^{\eta_c} \quad (5.3)$$

where: VoT_d is the value of time at distance d

VoT is the average value of time, 7.7833 p/min (Table A1.3.1 of the WebTAG databook, converted from £/hr)

η_c is the distance elasticity, 0.315

d_0 is the average London trip distance, derived from analysis of 2011 NTS data, of 8.2 km

For the work–work detour model, a log-cost formulation has been used instead of importing VoTs from WebTAG.

5.1.2. Car passenger cost sharing

For non-business purposes where both car driver and car passenger modes are available, tests were run to determine the appropriate car cost sharing proportions using Equation (4.2) and (4.3), based on the fit to the choices observed in the LTDS data. Table 10 summarises the results that were obtained. As noted in Section 4.3.2, for home–escort cost sharing was not tested due to a lack of car passenger data (the car passenger mode share is just 2.75 per cent).

Table 10. Car cost sharing factors

Purpose	Cost sharing factor S
commute	0.25
home–tertiary education	0.25
home–shopping	0.25
home–other travel	0.25
work–other tours	1
other–other tours	0.5
work–other detours	1
other–other detours	1

For commute, home–tertiary education, home–shopping and home–other travel, cost sharing values of S=0.25 gave the best fit to the data. These values imply that car passengers pay a proportion of the car cost but that the driver pays a higher share of the total.

For the two NWR tour models, the best results were obtained with higher values of S, implying passengers pay higher shares of the costs compared to HB travel. For the two NWR detour models, the best fit to the data was obtained with a value of S=1, implying that the passenger and driver pay an equal share of the total cost. This is a plausible result because the driver has to detour in order to serve the passenger travelling to the detour location and therefore there is a clear additional cost associated with the journey.

5.2. Level-of-service specification

The parking search time estimates were insignificant for most models and therefore not retained in the final model specifications. The one exception to this home–other travel, where a significant negative effect was identified. This means that overall the models will be insensitive to parking policy changes that influence search time. However, monetary parking costs form part of the car cost term for all travel purposes and so the models will still be sensitive to parking policy that changes parking costs.

To demonstrate the impact of merging parking costs with other car costs, a series of tests was undertaken for the final commute model specification. In the first test, a separate (linear) parking cost term was tested instead of adding parking costs to car costs. In the second test, parking costs were dropped from the model altogether. Table 11 summarises the impact on the model fit and cost parameters.

Table 11. Commute parking cost tests

	Final specification, parking costs merged with other monetary costs		Test 1: separate parking cost parameter		Test 2: parking costs dropped altogether	
Observations	8,365		8,365		8,365	
Log-likelihood	-54,045.1		-54,042.7		-54,065.6	
Degrees of freedom	49		50		49	
LogCost	-0.4767	-10.3	-0.4961	-10.4	-0.5238	-11.0
cost1t6	-7.77e-4	-8.1	-7.43e-4	-7.4	-7.61e-4	–7.5
cost78	-5.11e-4	-6.4	-4.60e-4	-5.6	-4.77e-4	-5.7
cost910	-1.90e-4	-2.7	-1.64e-4	-2.3	-1.78e-4	-2.4
PrkgCst			-0.0011	-6.0		

The separate parking cost parameter is negative and significant. However, this model specification implies that the marginal impact of a £1 increase in parking cost is different to the marginal impact of a £1 increase in other car costs. When parking costs are dropped from the model altogether, there is a loss of model fit of 20.5 log-likelihood units. This result demonstrates that including parking costs as part of total car cost helps to explain observed behaviour.

It was not possible to estimate separate parameters for each individual PT LOS component and therefore a series of tests was undertaken on the HB models to identify an acceptable specification for in-vehicle time (IVT) and out-of-vehicle time (OVT) components. Table 12 illustrates how terms have been merged to ensure that all components are included and that the estimated sensitivity parameters are plausible and significantly estimated for model specifications M1 to M6.

Table 12. Level-of-service specifications tested, home-based models

Level-of-service components	Model specification						
	Base	M1	M2	M3	M4	M5	M6
Rail IVT	✓	✓	✓		✓	✓	
Bus IVT	✓	✓	✓		✓	✓	
Crowding time	✓	✓					
Access/egress	✓						
Wait time	✓						
Boardings	✓						
Rail OVT		✓	✓	✓			
Bus OVT		✓	✓	✓			
Rail IVT + crowding				✓			
Bus IVT + crowding				✓			
Rail OVT + crowding					✓		
Bus OVT + crowding					✓		
PT OVT + crowding						✓	
Rail GenTime							✓
Bus GenTime							✓

An issue with the base specification was that crowding was wrongly signed across all HB purposes, possibly because people want to travel at the most crowded times and/or to busy destinations associated with crowded services. The weightings for boardings, wait time and access/egress time were correctly signed and significant for the majority of journey purposes but the relative values with respect to rail and bus IVT were quite different to the assignment assumptions.

In the M1 specification, merging the different OVT components into a single term[13] gave correctly signed OVT coefficients across all purposes but the crowding parameter remained wrongly signed and therefore problematic.

In the M2 specification, crowding was dropped altogether. This helped to improve the explanatory power for the OVT coefficients for business, primary education, escort and other travel purposes. However, the specification is not acceptable for policy testing because of the omission of any response in the model to changes in crowding.

Therefore in specification M3, crowding was merged with IVT. This had a significant impact on the rail IVT parameters, with the average value across purposes almost halving compared to the base specification, and this loss of explanatory power was not acceptable.

[13] Consistent with the assignment the OVT term applied equal weight to boarding penalties, initial wait time, interchange wait time and crowding time components, and weights of two to access and egress time and walk interchange time components.

In specification M4, crowding was merged with OVT. This resulted in slightly lower OVT parameters, but allowed crowding to be represented in the models without damaging the rail IVT parameter. Of the acceptable models (M4 to M6), this approach gave the best fit to the data.

In specification M5, rail and bus OVT were merged, which resulted in a significant loss of fit to the data compared to specification M4. However, this specification was adopted for all HB purposes except for home–escort because it gave a consistent weighting of OVT components for bus and rail. For home–escort, the rail IVT parameter was insignificant and weakly estimated and therefore unsuitable for policy testing.

In the M6 specification, the IVT and OVT terms were merged to give rail and bus generalised times. In general this specification led to a significant loss of fit to the data relative to the M5 specification but for home-escort this was the only specification that yielded acceptable model results and therefore specification M6 was adopted for home–escort tours.

For the six NHB purposes, the sample sizes were not sufficient for separate IVT and OVT terms to be estimated and therefore the M6 model specification was used. However, as noted in Section 5.1.1 the generalised bus and rail time terms in these models include contributions from monetary cost.

Table 13 summarises the final parameter estimates for the models that used the M5 specification. To allow comparison of variation in IVT sensitivities between modes, the car time parameters have also been included.

Table 13. PT IVT and OVT parameter estimates, M5 model specification

Purpose	Car time		Rail IVT		Bus IVT		PT OVT and crowding	
commuting	-0.034	-33.5	-0.012	-11.7	-0.028	-32.2	-0.010	-15.5
home–business	-0.032	-20.9	-0.006	-2.9	-0.023	-14.4	-0.011	-7.6
home–primary education	-0.073	-6.7	-0.039	-3.2	-0.054	-14.5	-0.020	-6.5
home–secondary education	-0.114	-19.7	-0.050	-7.7	-0.049	-22.9	-0.010	-7.0
home–tertiary education	-0.047	-9.0	-0.018	-6.9	-0.031	-18.3	-0.010	-7.9
home–shopping	-0.042	-68.5	-0.019	-4.9	-0.044	-26.6	-0.028	-15.8
home–other travel	-0.031	-92.3	-0.004	-2.2	-0.030	-26.6	-0.020	-16.9
work–work detours	-0.060	-15.1	-0.025	-3.3	-0.078	-7.7	-0.020	-3.8

It can be seen that the combined PT OVT and crowding estimates are significantly estimated for all purposes, though in most cases PT OVT and crowding minutes are weighted lower per minute than both rail IVT and bus IVT. However, the assignment weights are applied in the PT OVT calculations with weights of two for access and egress time and walk interchange components, and so we would not expect PT OVT values greater than the corresponding rail IVT and bus IVT values. The bus IVT parameters are consistently lower than the car time parameters but not dramatically so. However, the rail in-vehicle time parameters are much lower than the car time parameters. It is noted that low rail in-vehicle time parameters were observed in the current LTS model. These parameters will be influenced by high levels of car congestion for journeys to Central London, where rail is often chosen over car on the basis of journey time, as well as longer mean journey distances associated with travel by rail. The high costs of rail are also likely to play a role, as individuals choose rail for longer journeys even through the costs associated with the mode are high. The implication of the low rail time parameters is that the models will have a relatively low sensitivity to changes in rail IVT.

Table 14 summarises the PT IVT and OVT parameter estimates for the models that use the M6 model specification. It is noted that the home–escort model adds cost components for all modes to generalised car time, whereas for the NHB models the fare components for rail and bus are added to rail and bus generalised time.

Table 14. PT IVT and OVT parameter estimates, M6 model specification

Purpose	Car generalised time		Rail generalised time		Bus generalised time	
home-escort	-0.082	-60.2	-0.019	-5.9	-0.035	-17.8
work–work tours	-0.024	-12.3	-0.018	-5.9	-0.043	-5.7
work–other tours	-0.043	-9.6	-0.038	-5.4	-0.040	-4.8
other–other tours	-0.027	-9.5	-0.024	-2.9	-0.028	-8.6
work–other detours	-0.077	-51.5	-0.033	-25.5	-0.042	-18.5
other–other detours	-0.115	-72.6	-0.046	-22.7	-0.066	-40.6

Consistent with the results in Table 13, rail generalised time is weighted lower than the other modes, though for the NHB models where journey distances are shorter the differences are not as stark as those observed in Table 13 for the HB models.

5.3. Representation of cycling

As discussed in Section 4.5, tests were undertaken to investigate variation in the attractiveness of cycle between high cycle propensity (HCP) and low cycle propensity (LCP) groups. Differences were investigated both in terms of an HCP constant term and a term applied to the generalised cycle distance measure for the HCP group. The HCP generalised cycle distance term is expected to be positive, since we would expect HCP travellers to be less averse to increasing cycling distance than LCP individuals. Table 15 summarises the results from the tests for the HB models.

Table 15. Cycling propensity tests

Purpose	Constant for HCP group		Cycle generalised distance		Cycle generalised distance, additional effect HCP group	
commuting	1.3034	4.8	-0.1789	-17.8	0.0188	1.3
home–business	0.8578	1.9	-0.2292	-9.0	0.0545	1.6
home–primary education	3.0879	4.1	-0.9580	-8.8	no term	
home–secondary education	no term		-0.6631	-4.6	no term	
home–tertiary education	0.8108	1.3	-0.2267	-6.4	0.0634	1.3
home–shopping	11.1309	4.4	-0.7614	-12.8	no term	
home–escort	5.3308	3.4	-0.9282	-7.3	no term	
home–other travel	7.9261	5.0	-0.4527	-20.3	no term	
work–work tours	no term		-1.2400	-2.7	no term	
work–other tours	no term		-1.0800	-3.5	no term	
other–other tours	no term		-1.0448	-2.0	no term	
work–work detours	no term		-0.4897	-5.6	no term	
work–other detours	no term		-0.3791	-9.8	no term	
other–other detours	no term		-0.8032	-11.6	no term	

For commuting, home–business and home–tertiary education, it has been possible to estimate positive generalised cycle distance terms that reflect lower disutility per minute of generalised cycle time in addition to positive HCP constants reflecting a higher preference for cycling among the HCP group. These parameters are applied additionally to the cycle generalised distance terms, which are estimated across both LCP and HCP groups. It is noted that these terms are not statistically significant at a 95 per cent confidence interval but have been retained in the models because they give plausibly moderate reductions in the aversion to generalised cycle distance in the HCP group.

For home–primary education, home–shopping, home–escort and home–other travel, cycle distances are shorter, shown by the larger magnitudes of the cycle generalised distance parameters, and for these purposes it was not possible to identify an additional generalised cycle distance effect for the HCP group. However, large positive HCP constants have been estimated for all four of these models, reflecting much higher cycle use in the HCP group relative to the LCP group.

No significant HCP effects have been identified in the NHB models. The sample sizes are much smaller for the NHB models and this means there are fewer data to allow the HCP effects to be identified. Nonetheless significant generalised cycle distance terms estimated across both HCP and LCP groups have been identified that show that the utility of cycling decreases strongly with increased tour distance.

In summary, for all the HB purposes except home–secondary education, the mode-destination model estimation was able to capture differences in preferences for cycling between LCP and HCP groups. In forecasting, moving more population to the HCP group will result in increased cycle demand, and for the three purposes with HCP generalised cycle distance terms (i.e. commute, home–business and home–tertiary education), increases in mean cycle distances.

5.4. Segmentation terms

Table 16 summarises the segmentation parameters in the final HB model specifications. Full details of the segmentation terms present in each of the models are given in Appendix B, where the model parameter results are presented in full.

Table 16. Segmentation effects present in the home-based model specifications

Purpose	Car availability	Gender	Age	Employment status	Occupation	PT pass ownership	Disability	Household income	Household type
commute	√	√	√	√	√			√	
business	√	√	√	√	√	√			
primary education	√								
secondary education						√		√	
tertiary education	√	√	√				√		√
shopping	√	√	√	√	√			√	
escort	√	√	√	√	√				√
other travel	√	√	√	√	√		√		√

It can be seen that travellers' preferences have been found to vary over a wide range of socio-economic dimensions. Representing all of these effects would have led to unfeasibly high model run times and the segmentation report discusses which of these terms have been implemented as explicit segmentation variables in the model and which have been implemented by representing the mean contribution observed in the base estimations.

The sample sizes for the NHB tour and detour models were much smaller and therefore far fewer segmentation effects were identified. Initially car availability, age, employment status, occupation and household income segmentation terms were identified. However, some of these terms were removed following the segmentation review on the basis that they had only a moderate impact of mode share and that implementing them in the model would significantly complicate the NHB implementation. Table 17 summarises the socio-economic effects present in the final NHB models.

Table 17. Segmentation effects present in the non-home-based model specifications

Purpose	Home-based tour mode	Car availability	Age	Employment status	Occupation
work–work tours	√				
work–other tours	√				
other–other tours	√				
work–work detours	√			√	√
work–other detours	√	√			
other–other detours	√		√	√	

The ‘home-based tour mode’ terms reflect that if an individual chooses a mode for their HB tour then that mode is more likely to be used for the associated NHB tour or detour. It can be seen that they are present in all six NHB models and are the most important segmentation in the NHB models in terms of explaining mode choice. These HB tour mode terms have been implemented directly. Some further segmentation terms are present in the three detour models and these have been implemented using average effects rather than by representing separate segmentations, which would have significantly complicated the implementation of the NHB models.

The car availability parameters are particularly important in capturing the probability of an individual choosing the car driver and car passenger alternatives, and furthermore some car availability effects have been identified for PT and active modes. Table 18 summarises the effects present in the HB model specifications. Plusses and minuses in the table indicate whether the effect means that the individual is more or less likely to choose the mode. It is noted that the car availability terms were tested after the car passenger distance term had been tested and after the car cost sharing tests had been run.

Table 18. Car availability effects present in the home-based model specifications

Purpose	Car driver			Car passenger			Train		Bus				Cycle			Walk	
	One car, free car use	One car, car competition	Two-plus cars, free car use	Passenger opportunity	Car, no licence	No car households	Car, no licence	One car, car competition	Car, no licence	No car in household	One car, car competition	Two-plus cars, free car use	Car, no licence	One car, car competition	2+ cars, car competition	No car in household	One car, car competition
commute	+	–	+	+	+				+				–				
business			+	+				+						+			
primary education										+						+	
secondary education										+[14]							
tertiary education						–		+									
shopping	+			+				+		+		–	–				+
escort		–		+						+	–	–			+		
other travel				+			–	+		+		–		+			+

[14] For secondary education, this term has been specified the other way around as 'household owns at least one car'.

It is noteworthy that a substantial number of car availability effects have been identified on PT and active modes as well as on the car driver and car passenger. A key effect is the passenger opportunity terms on car passenger, which reflect much higher chances of choosing car passenger when another household member can offer a lift. Bus usage is consistently higher in zero car households than in car-owning households. Interestingly cycling usage is higher for individuals who have a licence but where competition for cars exists in the household. The terms on walk also demonstrate higher propensity to walk for households with lower levels of car availability.

5.5. Origin and destination effects

5.5.1. Mode and destination choice effects

Both the commute and home–business models capture higher rail use to high employment density areas such as Canary Wharf using an employment density term. Furthermore, the business model includes a positive term on rail that is applied for all zones in the London Congestion Charge Zone. Together these effects ensure that the models capture the high levels of rail use to access Central London destinations.

The shopping model includes population density destination effects. These terms reflect higher levels of bus use, and lower levels of rail use, to the most densely populated areas. The escort model includes two origin population density effects, one for train and one for walk: the terms reflect higher use of these modes for travel from higher population density origins. The other travel model incorporates population density destination terms, with both rail and bus use more likely to the most densely populated zones relative to the other modes. The model further includes a number of origin population density interaction effects, which show that car passenger is more likely to be chosen in less densely populated origin zones, and PT and active modes are more likely to be chosen in more densely populated origin zones, relative to car driver.

5.5.2. Size variables

The shopping model uses both retail employment and retail floorspace (in square metres divided by 1,000) as attraction variables and the estimated size term for retail floorspace shows it has a similar impact per unit to the retail employment attraction variable.

The escort model uses four size variables: population (the base term), primary enrolments, secondary enrolments and tertiary enrolments. The estimated parameters showed that primary enrolments have the greatest impact, with the size term showing a per-unit impact 26.0 times that of population. The corresponding per-unit values for the secondary and tertiary attractions are 8.9 and 5.1 respectively. These results are consistent with the fact that most primary education children are escorted to and from school whereas only a fraction of secondary and tertiary aged students are escorted. The escort model also includes origin population effects for train and walk, reflecting higher use of the modes for tours originating in more densely populated areas.

The other travel model uses population as the base size variable and then estimates a size term for service employment. The results show that the per-unit impact of service employment is 46 times higher than population, i.e. service employment gives a much better explanation of other travel destination choice than population.

The four non-work-related NHB models all used population as a base size variable and then estimated size terms for service employment, as well as retail employment for the two detour models. The estimated size parameters also show that the per-unit impact of both service and retail employment is consistently much higher than that of population.

5.6. Structural tests

As illustrated in Section 4.7, the structural tests incorporated sub-mode nests for PT modes and active modes. However, the only travel purpose where a significant sub-mode effect was identified was the commute model, where the structural tests yielded a structure with main modes above simultaneous PT modes and destinations with a nesting parameter of 0.75 (t=6.7). This structure ensures higher cross-elasticities between PT modes than across PT modes and non-PT modes in contrast to a structure with PT modes represented at the same level as the other modes. However, no active mode nest effect was identified in the commute model.

For the remaining HB purposes, it was not possible to identify either PT or active mode nests and the resulting nesting structures that gave the best fit to the observed choices reflected modes above destinations. Table 19 summarises the nesting parameters that have been estimated. The nesting parameters express the relative sensitivity of mode and destination choices with a value of 1 implying that mode and destination choices are equally sensitive to changes in utility, whereas values close to 0 imply that destination choice is much more sensitive to changes in utility than mode choice. The t-statistics show the significance of the nesting parameters relative to values of 1 and 0.

Table 19. Mode-destination nesting parameters

Purpose	Mode-destination nesting parameter		
	value	t-ratio wrt 1	t-ratio wrt 0
home–business	0.86	1.4	8.6
home–primary education	0.53	8.1	9.1
home–secondary education	0.78	2.5	8.9
home–tertiary education	1.00	n/a	n/a
home–shopping	0.12	88.6	12.1
home–escort	0.11	34.6	4.3
home–other travel	0.12	79.1	10.8
work–work tours	0.20	6.7	1.7
work–other tours	0.39	4.1	2.6
other–other tours	0.42	4.9	3.6
work–work detours	1.00	n/a	n/a
work–other detours	0.26	4.3	1.5
other–other detours	1.00	n/a	n/a

For the home-tertiary education model it was not possible to estimate a significant nesting parameter and therefore the structural parameter was constrained to a value of 1.

The mode nesting parameters are much stronger for the discretionary travel purposes of shopping, escort and other travel where the cost specification was transferred from the commute model. The practical implication, which seems plausible, is that the response to cost changes for discretionary travel will show higher levels of destination switching and lower levels of mode switching, relative to the other travel purposes.

6. Nested logit model validation

This chapter presents a validation of the implied VoTs and model elasticities. These measures are important because they provide an assessment of how the models will respond to policy when the implemented models are used for forecasting, and we expect the model VoTs and sensitivities to be in line with other evidence on model sensitivity.

Validation of tour and detour lengths is also presented. This is somewhat less important than for VoTs and elasticities because the models will be applied incrementally to predict changes relative to a base matrix, and the base matrix should represent trip lengths accurately. Nonetheless we expect the trip lengths to provide a good match to the observed LTDS data used for model estimation, and furthermore the model sensitivity that feeds into the incremental application will be strongly dependent on trip length.

6.1. Values-of-time

It is worth noting that the WebTAG VoTs we have validated the implied model VoTs against incorporate limited variation in respect to mode and purpose as they are intended primarily for appraisal purposes.

The implied VoTs for each mode vary as a function of the sensitivity to IVT, the sensitivity to cost and, for most purposes, the cost of the journey. All VoTs presented in this section are in 2011 prices and values and the costs and times relate to tour costs, i.e. outbound plus return.

In the commute model, separate linear and log-cost parameters were estimated and the linear cost parameters varied by income band. Equation (6.1) shows how the implied VoTs have been calculated.

$$VoT_{m,I}(cost) = \frac{\partial U / \partial IVT}{\partial U / \partial \text{cost}} = \frac{\beta_{IVT,m}}{\beta_{cost,I} + \dfrac{\beta_{LogCost}}{Cost}} \tag{6.1}$$

where: $\beta_{IVT,m}$ is the IVT parameter for the mode m

$\beta_{cost,I}$ is the cost parameter, which varies by income band I

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

cost is the cost of the journey

The IVT parameters vary between mode and therefore separate VoT curves are plotted by mode as well as by income band. These are plotted in the following three figures.

Figure 8. Commute implied VoTs for car driver

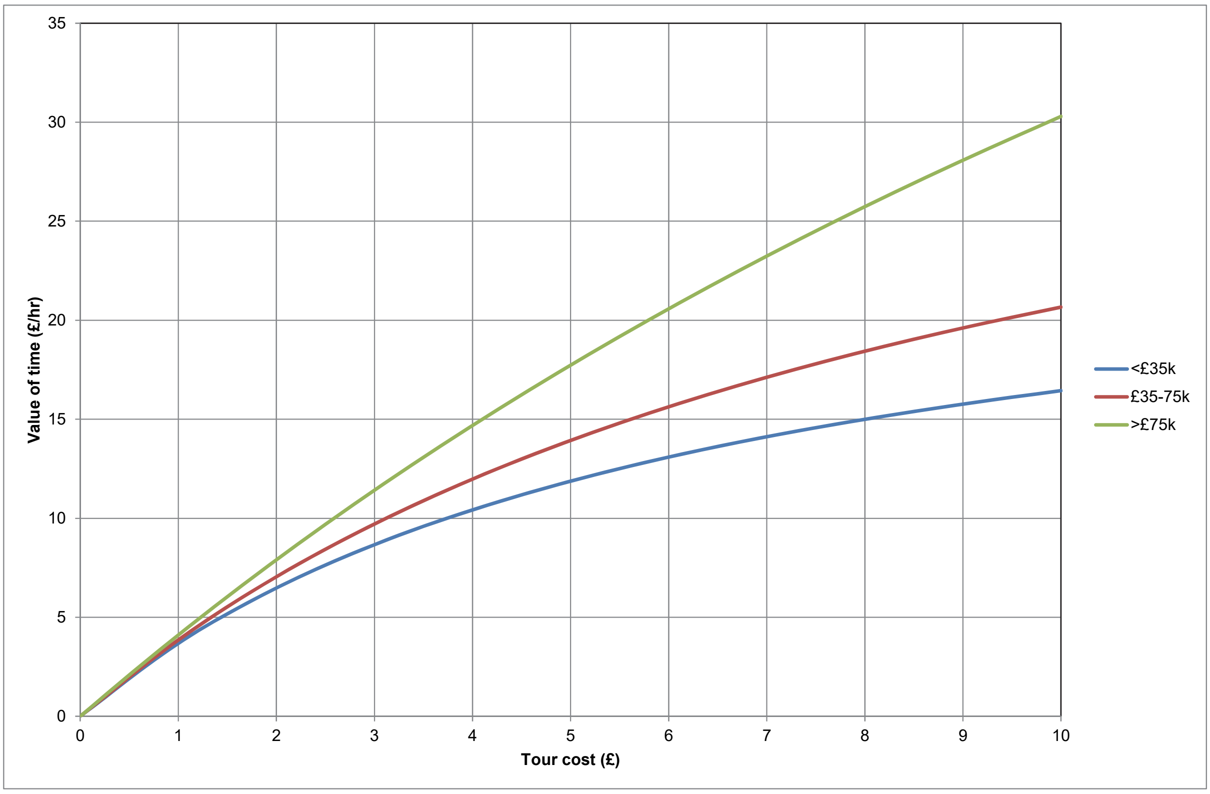


Figure 9. Commute implied VoTs for rail

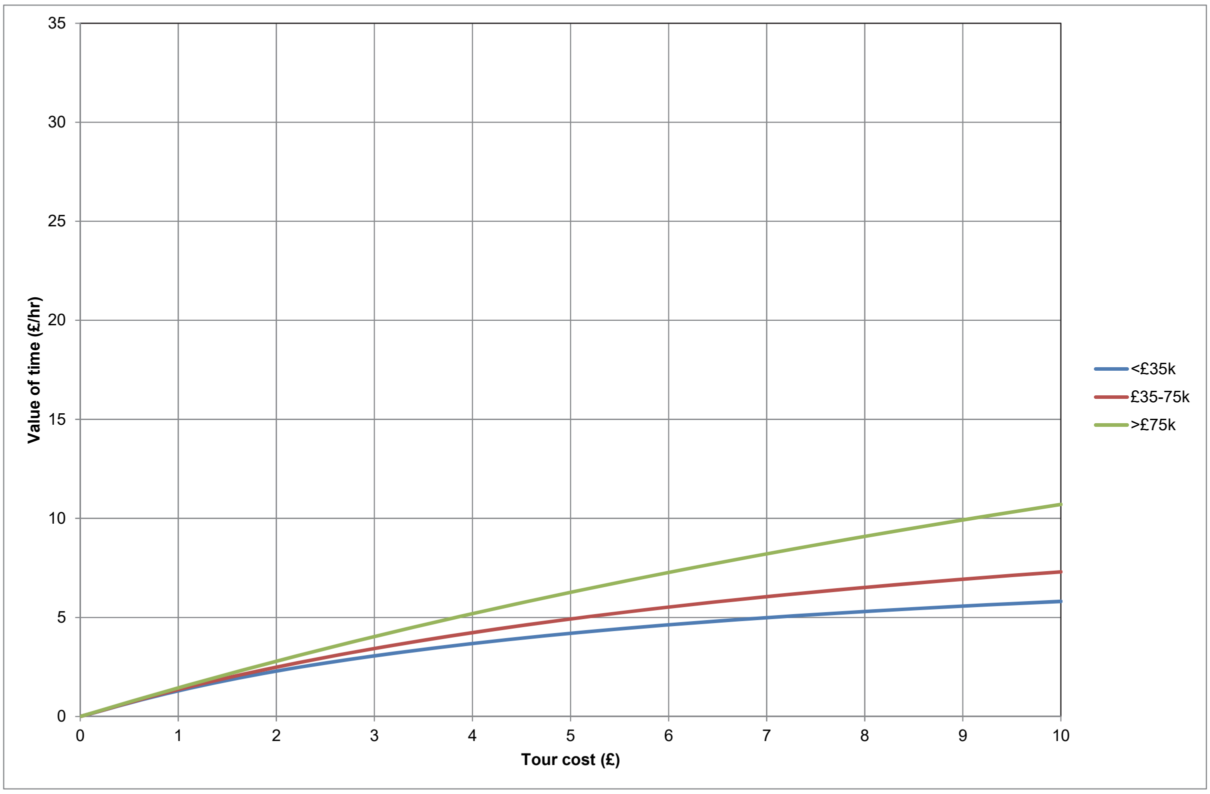
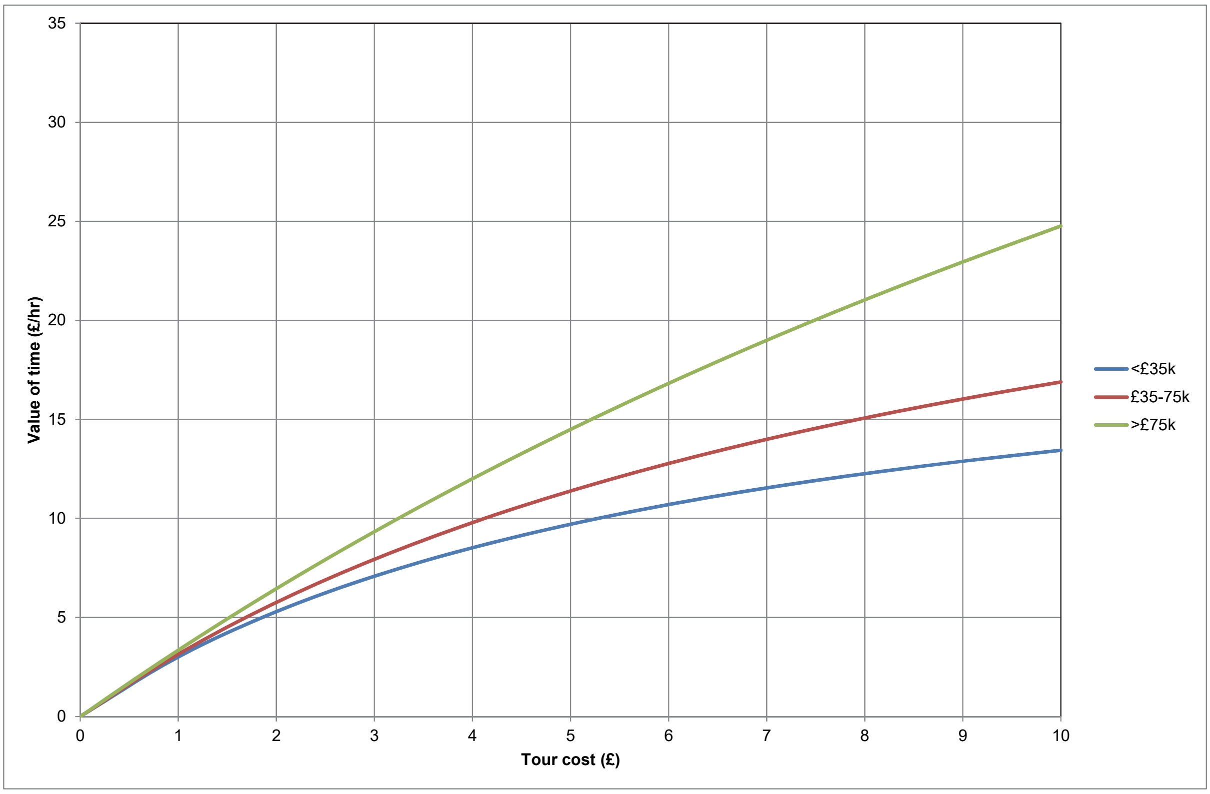


Figure 10. Commute implied VoTs for bus



To provide a comparison to the WebTAG guidance values, the median observed costs for each mode for the chosen destinations were used as representative costs to enable calculation of observed VoT values. This comparison is presented in Table 20.

Table 20. Comparison of commute VoTs at median mode cost to WebTAG

		Median cost (£)	Values of time (£/hr)		
			Household income <£35k p.a.	Household income £35–75k p.a.	Household income £75k+ p.a.
WebTAG	all modes	n/a	10.22	10.22	10.22
modelled by mode	car driver	3.18	9.01	10.15	12.03
	rail	5.57	3.19	3.59	4.25
	bus	2.60	7.37	8.30	9.83

The car driver and bus VoTs at the median costs are consistent with the WebTAG guidance values. However, rail VoTs are significantly lower, which follows from the low value of the rail IVT parameter.

For the home–business model, a gamma formulation was used. Equation (6.2) shows how implied VoTs have been calculated for this model.

$$VOT = \frac{\partial U / \partial \text{time}}{\partial U / \partial \text{cost}} = \frac{\beta_{time}}{\beta_{\cos t}\left\{\gamma + \frac{(1-\gamma)}{\text{cost}} \cdot \frac{\text{E(cost)}}{\text{E(log(cost))}}\right\}} \tag{6.2}$$

where: β_{time} is the IVT parameter for the mode

β_{cost} is the cost parameter, which varies by income band

γ controls the relative contribution of linear and logarithmic cost

E(cost) is the mean cost

E(log(cost)) is the mean logarithmic cost

The ratio E(cost)/E(log(cost)) ensures linear and logarithmic cost use the same overall scale.

The following figures plot the variation in the home–business VoTs with the tour cost for car driver, rail and bus modes respectively. It can be seen that the variation in VoT with income band is relatively moderate whereas the variation in VoT with tour cost is strong, with a relationship to tour cost that is close to linear. This follows from the low gamma value for this purpose (0.01), which means that the log cost effect is much stronger than the linear cost effect. Note that with a gamma value of 0 (i.e. a logarithmic form), VoT would be directly proportional to cost.

Figure 11. Home–business implied VoTs for car-driver

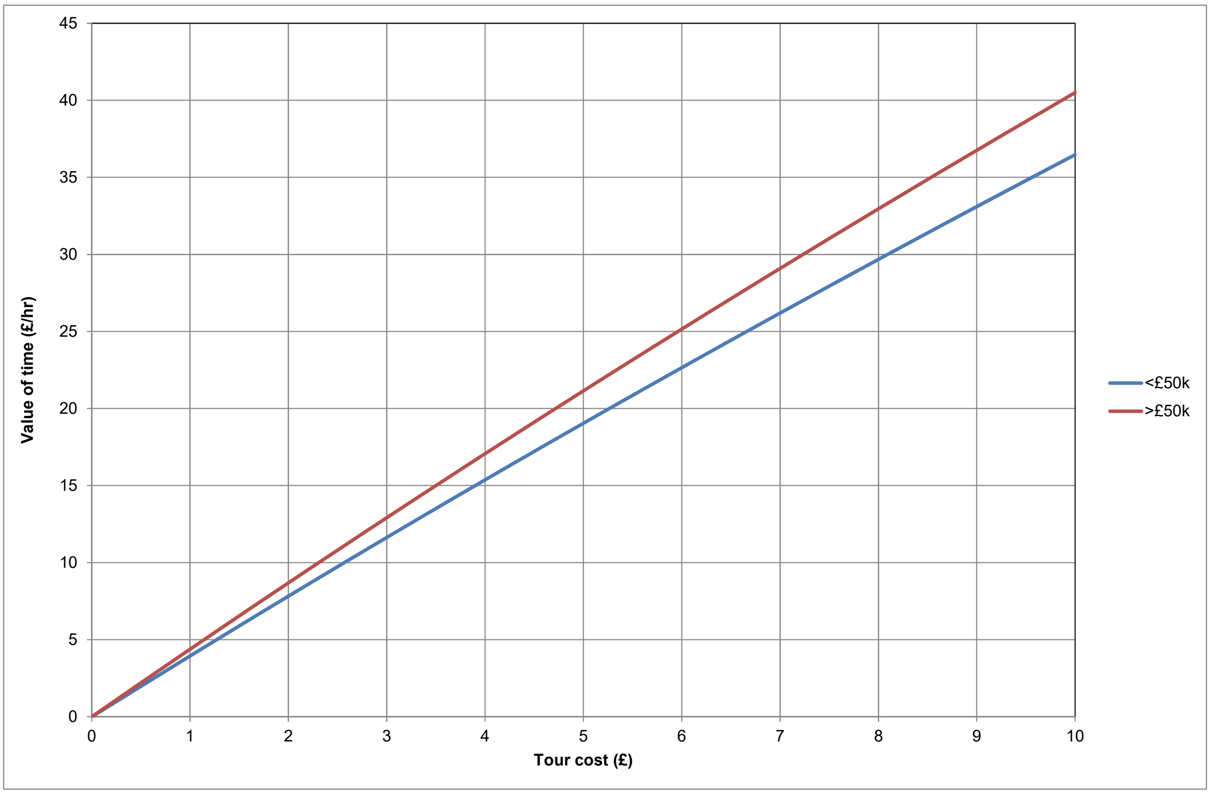


Figure 12. Home–business implied VoTs for rail

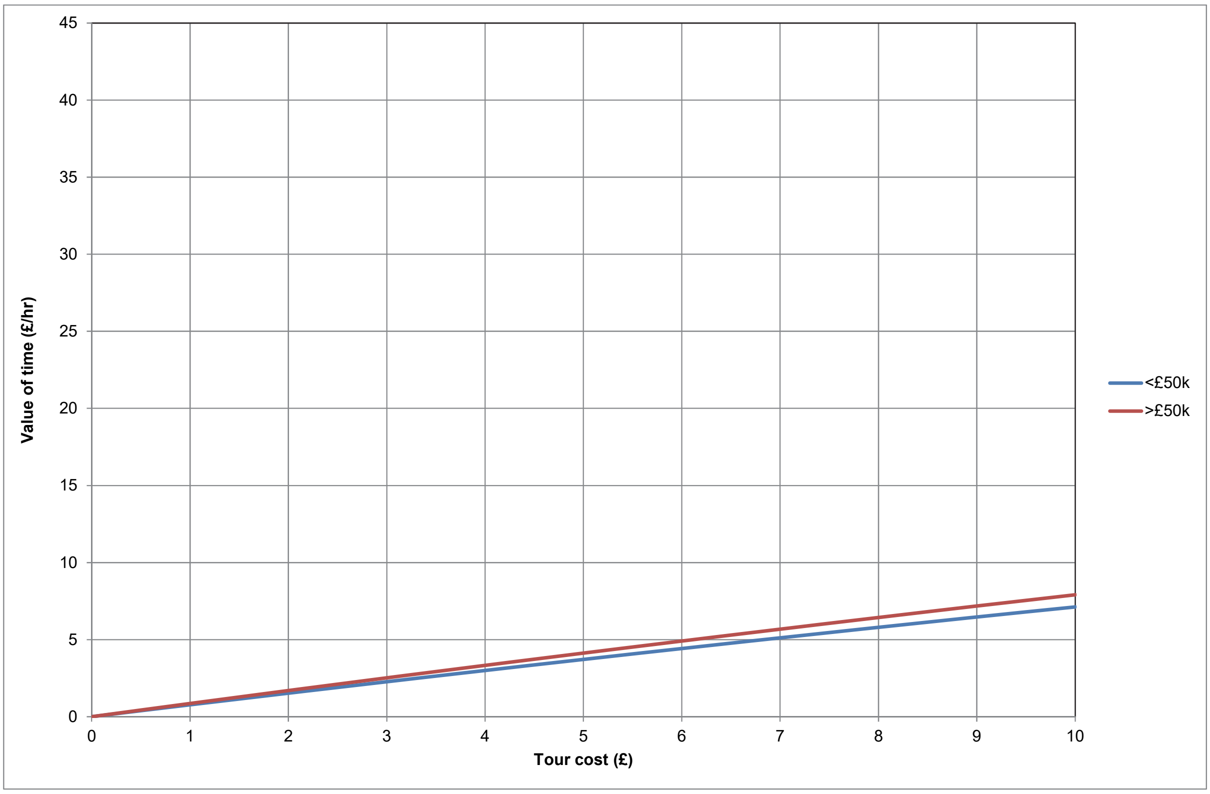
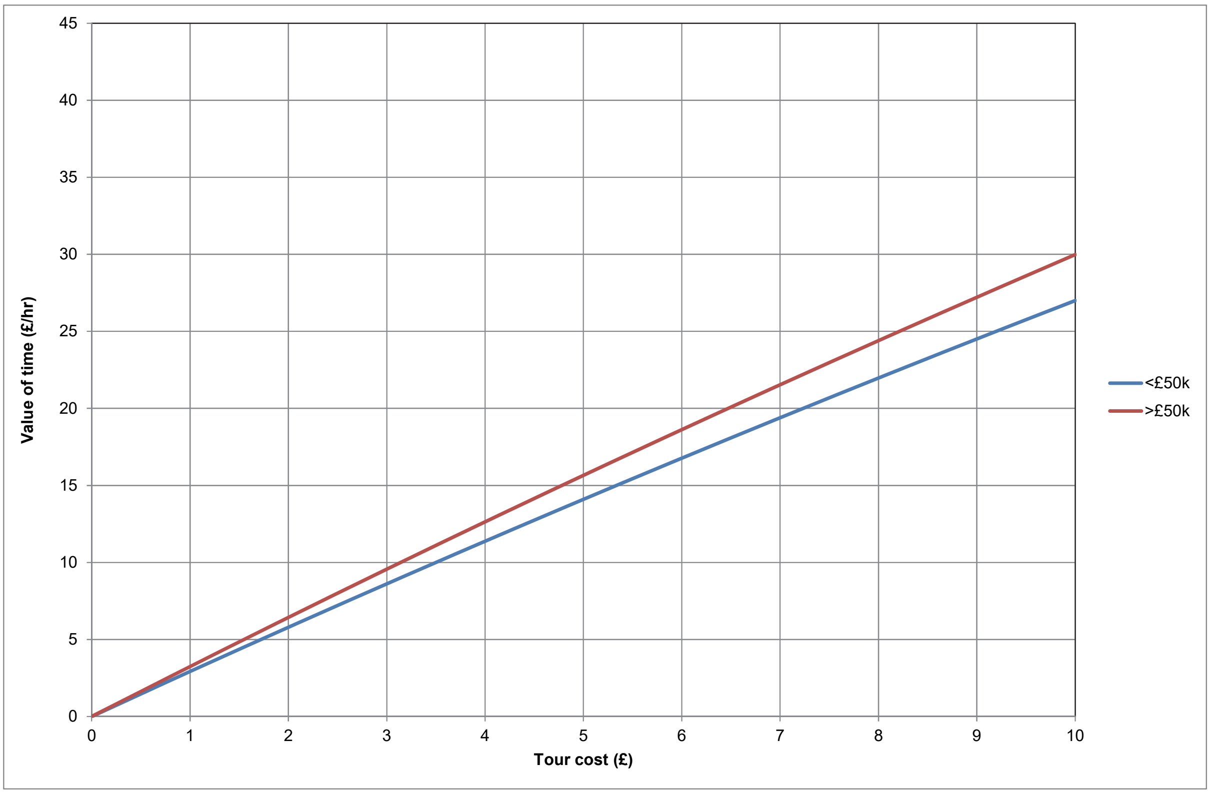


Figure 13. Home–business implied VoTs for bus



To provide a comparison to the WebTAG guidance values, the median costs for the chosen mode-destinations were used. This comparison is presented in Table 21.

Table 21. Comparison of business VoTs at median mode cost to WebTAG

		Median cost (£)	Values of time (£/hr)	
			Household income <£50k p.a.	Household income £50k+ p.a.
WebTAG	all modes	n/a	16.63	16.63
Modelled by mode	car driver	3.51	13.55	15.04
	rail	5.28	2.65	2.94
	bus	2.37	10.03	11.14

At the median costs the car VoTs are consistent with the WebTAG all-mode values. Bus VoTs are around two-thirds of the WebTAG values whereas the rail VoTs are much lower, a consequence of the small rail IVT parameter.

No costs are represented in the home–primary education and home–secondary education models and therefore no VoTs are presented for these models.

The tertiary education model estimated separate linear cost and log cost parameters like the commute model. Equation (6.1) has been used to plot the VoTs for each mode. Figure 14 plots the variation in the implied VoTs by mode with the cost of the tour.

Figure 14. Home–tertiary education implied VoTs by mode

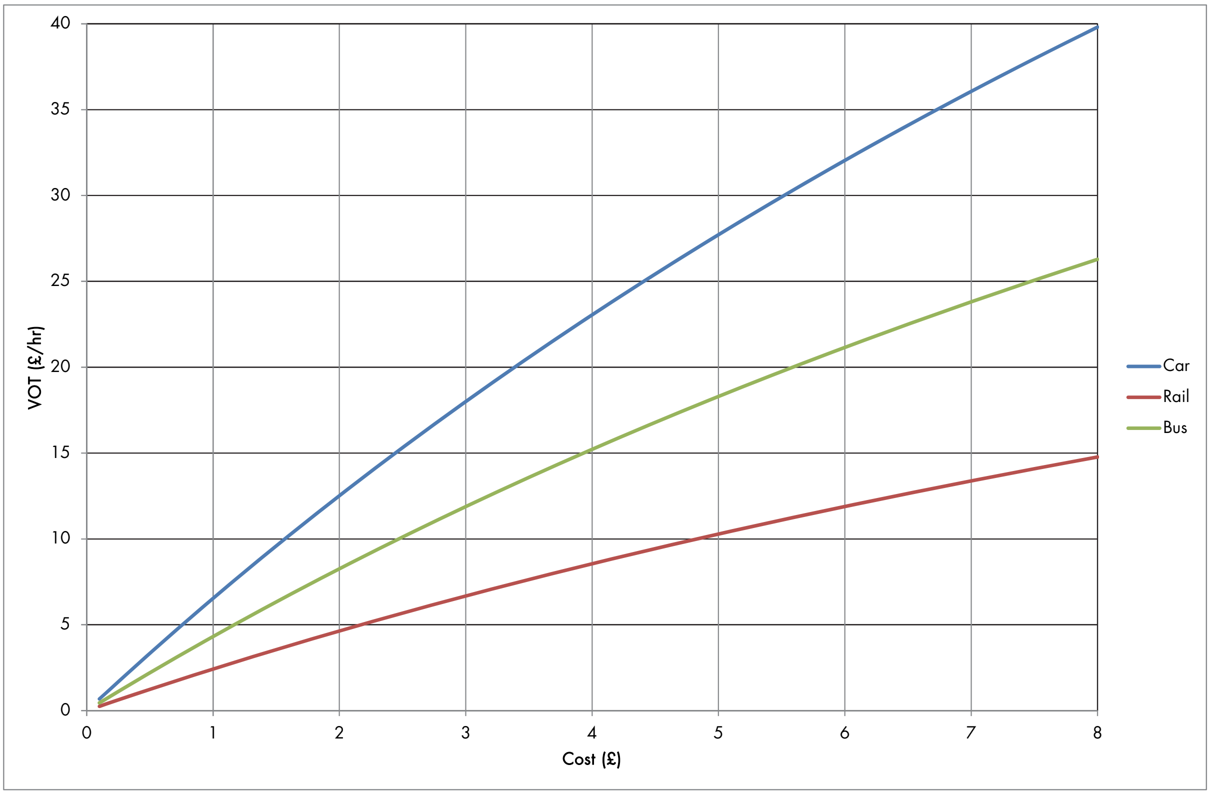


Table 22 presents a comparison of the VoTs at the median costs against the WebTAG guidance values.

Table 22. Comparison of home–tertiary education VoTs at median mode cost to WebTAG

		Median cost (£)	Value of time (£/hr)
WebTAG	all modes	n/a	4.67
Modelled by mode	car driver	2.05	12.82
	rail	3.50	4.76
	bus	1.82	8.46

At the median costs the rail VoTs are consistent with the WebTAG guidance values whereas the values for car driver and bus are higher.

The shopping, escort and other travel models also use the commute cost sensitivity parameters, but the VoTs are rescaled by the ratio of commute and other VoTs in WebTAG as well as by the ratio of the model car time parameters to correct for scale differences. Therefore the VoT distributions have the same shape as those for commute presented above but have a rescaling factor applied. The following tables present the comparisons of the implied VoTs at the median mode costs for these purposes.

Table 23. Comparison of home–shopping VoTs at median mode cost to WebTAG

		Median cost (£)	Values of time (£/hr)		
			Household income <£35k p.a.	Household income £35–75k p.a.	Household income £75k+ p.a.
WebTAG	all modes	n/a	4.67	4.67	4.67
Modelled by mode	car driver	1.27	2.53	2.69	2.91
	rail	2.80	2.08	2.33	2.73
	bus	1.82	3.58	3.89	4.33

The median shopping VoTs are somewhat lower than the WebTAG guidance values, particularly for rail. This is due to lower tour distances for shopping compared to commuting (the source of the cost function transferred to home–shopping). At the mean commute tour distances we would expect higher VoTs close to the WebTAG guidance values.

Table 24. Comparison of home–escort VoTs at median mode cost to WebTAG

		Median cost (£)	Values of time (£/hr)		
			Household income <£35k p.a.	Household income £35–75k p.a.	Household income £75k+ p.a.
WebTAG	all modes	n/a	4.67	4.67	4.67
Modelled by mode	car driver	1.35	2.16	2.30	2.50
	rail	4.05	0.91	0.97	1.06
	bus	2.60	2.20	2.35	2.55

As per the shopping results, we observe lower VoTs than WebTAG guidance values for escort travel because of the way the transferred commute cost function operates when mean escort tour distances are lower than those in the commute model used for the transfer. Rail VoTs are again lowest due to the lower rail IVT parameter.

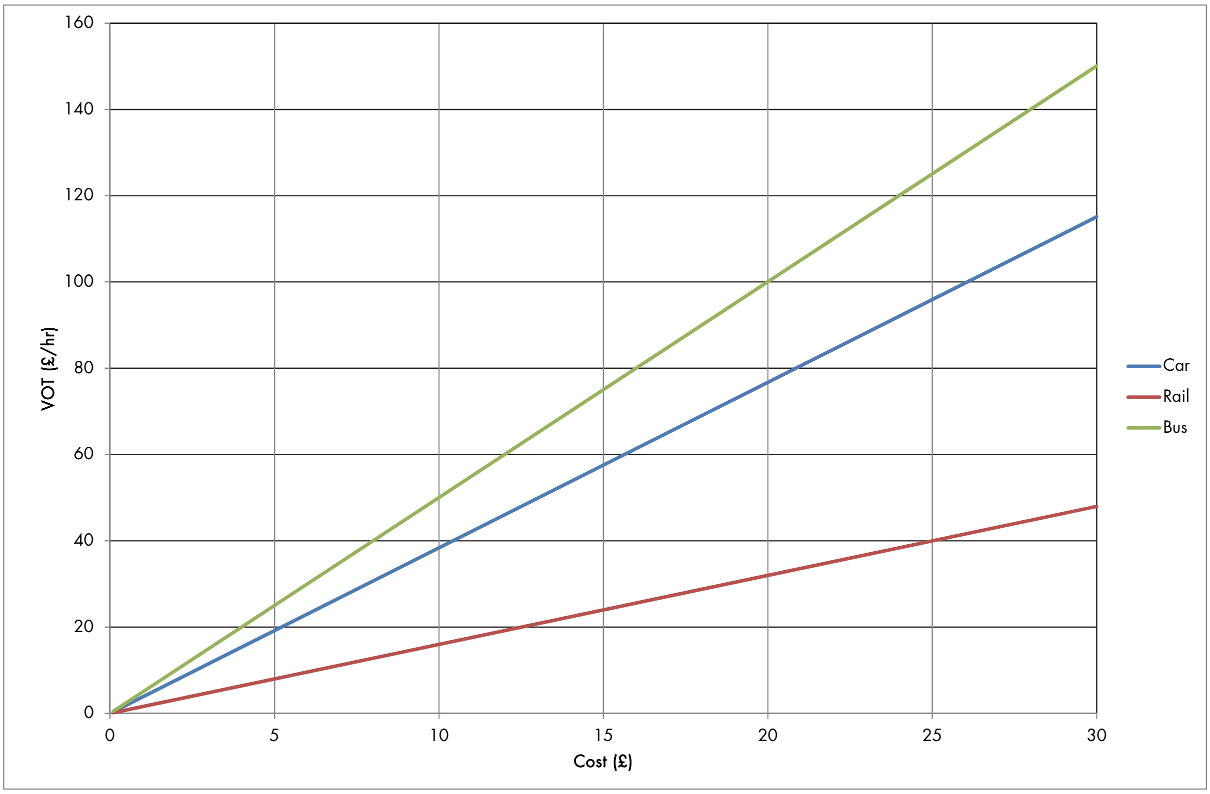
Table 25. Comparison of home–other travel VoTs at median mode cost to WebTAG

		Median cost (£)	Values of time (£/hr)		
			Household income <£35k p.a.	Household income £35–75k p.a.	Household income £75k+ p.a.
WebTAG	all modes	n/a	4.67	4.67	4.67
Modelled by mode	car driver	2.09	2.81	3.08	3.48
	rail	4.20	0.54	0.63	0.78
	bus	2.00	2.61	2.85	3.21

For other travel, the car driver and bus the VoTs are somewhat lower than WebTAG guidance values due to lower tour distances compared to commute, but not dramatically so. However, the rail values are much lower, which follows from the small rail IVT parameter estimate for other travel.

For five of the six NHB purposes, VoTs were imported from WebTAG and so no implied VoTs are presented here. However, the work–work detour model estimated a log cost term and so VoTs for this purpose are illustrated below.

Figure 15. Work–work detour model implied VoTs by mode



With the log cost formulation the VoTs increase linearly with distance. The rail VoTs are lower than the other two models because the IVT parameter is significantly smaller in magnitude.

Table 26. Comparison of work–work VoTs at median mode cost to WebTAG

		Median cost (£)	Value of time (£/hr)
WebTAG	all modes	n/a	16.63
Modelled by mode	car driver	2.70	10.43
	rail	2.00	3.20
	bus	2.60	13.01

The VoTs are lower than the WebTAG overall average values of £16.63 per hour, which follows from the fact that detours are short and therefore the costs are lower than would be incurred for longer business journeys. It is noted that for journeys in the 0–50 km distance band, the WebTAG guidance value for car driver is £8.65 per hour, which is closer to the implied car driver value in Table 26.

For purposes other than commute and business, there is a tendency for VoTs to be lower than the WebTAG guidance values. The implication of this is that we would expect the models to be more sensitive to cost changes relative to models with higher VOTs.

In summary, the commute and home–business VoTs again validate WebTAG guidance for car driver and bus, with lower values for rail due to the small rail IVT parameters. For the home–shopping, home–escort and home–other travel models, the implied VoTs are lower than WebTAG guidance for all modes, which is a consequence of transferring the commute cost function to purposes with lower mean trip lengths. The implication for model application of the low VoTs is relatively high sensitivity to changes in cost for those modes with low VoTs relative to sensitivity to changes in IVT.[15] However, as Section 6.2 demonstrates, there is no evidence that the high cost sensitivity associated with low VoTs has resulted in high elasticities to fuel cost and fare changes.

6.2. Model elasticities

Elasticity validation tests have been run for four policy tests:

- A 10 per cent increase in fuel cost
- A 10 per cent increase in car time
- A 10 per cent increase in PT fares, including both cash fares and season tickets
- A 10 per cent increase in PT IVT.

The 10 per cent increases are applied uniformly across all OD pairs. The elasticities are then calculated using the constant elasticity formulation:

[15] The VoT measures the ratio of the relative sensitivities of IVT and cost.

$$E_{m,p} = \frac{\ln\left(\frac{D_{m,p}}{D_{m,b}}\right)}{\ln\left(\frac{110}{100}\right)} \tag{6.3}$$

where: $E_{m,p}$ is the elasticity for mode m under policy p

$D_{m,p}$ is the demand for mode m under policy p

$D_{m,b}$ is the demand for mode m in the base case b

It should be emphasised that the elasticities are first order elasticities only; they do not take into account network effects. When the models are applied iteratively, so that changes in demand impact on the supply costs, the fuel cost elasticities would be expected to be slightly lower because of network effects damping the model response.

It is also emphasised that the elasticity calculations have been made with external destinations set to be available, whereas in the model estimation external destinations were only available for commute. External destinations were set to be available to ensure that the elasticities are comparable with the realism tests that will be run once the models have been implemented in CUBE, these will include trips to external destinations.

Table 27 summarises the fuel cost and car time elasticities by fuel purpose.

Table 27. Car driver fuel cost and car time elasticities by purpose

Purpose	Tours/detours		Kilometres	
	Fuel cost	Car time	Fuel cost	Car time
commuting	-0.12	-0.58	-0.21	-1.43
home–business	-0.04	-0.56	-0.05	-1.31
home–tertiary education	-0.13	-1.25	-0.13	-2.31
home–shopping	-0.04	-0.05	-0.18	-0.71
home–escort	-0.03	-0.04	-0.17	-0.82
home–other travel	-0.04	-0.06	-0.22	-0.84
work–work tours	-0.03	-0.10	-0.29	-1.02
work–other tours	-0.17	-0.56	-0.42	-1.45
other–other tours	-0.14	-0.42	-0.40	-1.20
work–work detours	-0.02	-0.08	-0.04	-0.98
work–other detours	-0.01	-0.04	-0.23	-0.83
other–other detours	-0.07	-0.19	-0.31	-0.99
Total elasticity	-0.06	-0.24	-0.19	-1.09

The total elasticity values are weighted average values, with the contribution from each journey purpose weighted by either the total number of tours/detours or by the total kilometres.

As would be expected, home–business has a lower fuel cost elasticity that the other HB purposes, and the work–work detour model has a similarly low elasticity value.

WebTAG guidance is that the overall fuel cost kilometrage elasticity should lie within the -0.25 to -0.35 range, whereas the overall elasticity observed across the models is -0.19; the elasticity of the models to fuel cost changes is therefore low relative to WebTAG guidance. There are a number of factors that may contribute to this difference. The WebTAG guidance fuel cost elasticities are based on 2002 analysis and real increases in income since then would be expected to have led to a reduction in fuel cost elasticity. A further consideration is that average incomes in London are above the national average and this would also be expected to lead to lower fuel cost elasticity values. Finally, for home–shopping, home–escort and home–other travel, we observe fuel cost elasticities that are similar to the commute values, which follows from the transfer of the commute cost function to these purposes. Normally we would expect higher elasticities for discretionary travel purposes and this is the expectation set out in WebTAG.

WebTAG guidance on car trip time elasticities is simply that they should be checked to ensure none is stronger than -2.0. This condition is met for all of the HB and NHB models. The lowest car time elasticities are observed for home–shopping, home–escort and home–other travel purposes.

The PT fare and IVT elasticities are presented in Table 28. Note that fare elasticities are not presented for home–primary education and home–secondary education since these models do not have a cost term (because travel by PT is free for primary- and secondary-aged children).

Table 28. PT fare and in-vehicle time elasticities by purpose

Purpose	Tours/detours		Kilometres	
	fare	IVT	fare	IVT
commuting	-0.23	-0.32	-0.36	-0.55
home–business	-0.19	-0.32	-0.20	-0.44
home–primary education	n/a	-0.63	n/a	-1.23
home–secondary education	n/a	-0.62	n/a	-1.32
home–tertiary education	-0.11	-0.50	-0.12	-0.93
home–shopping	-0.07	-0.09	-0.09	-0.47
home–escort	-0.11	-0.09	-0.18	-0.47
home–other travel	-0.07	-0.08	-0.17	-0.29
work–work tours	-0.08	-0.10	-0.31	-0.72
work–other tours	-0.67	-0.37	-0.67	-0.82
other–other tours	-0.14	-0.39	-0.20	-0.87
work–work detours	-0.24	-0.24	-0.24	-0.75
work–other detours	-0.11	-0.08	-0.36	-0.60
other–other detours	-0.32	-0.55	-0.37	-0.98
Total elasticity	-0.16	-0.28	-0.28	-0.56

The WebTAG guidance for PT fare elasticities is that they should lie in the -0.2 to -0.9 range. The overall elasticity is -0.16, so somewhat lower than that. The total elasticity values are calculated as a weighted average and the key contributors to the low elasticity are the home–shopping, home–escort and home–other travel models, where the cost sensitivity function was transferred from the commute model. If future estimation work was to be undertaken it is recommended to revisit the cost specification for these models with the aim of realising higher elasticity values for both fuel cost and PT fare.

No WebTAG guidance elasticities are given for PT IVT. The values are generally reasonable but home–shopping, home–escort and home–other travel have low values that are worth revisiting in any future estimation work.

In summary, the model elasticity validation showed the models to be somewhat inelastic to changes in fuel cost and PT fare. The discretionary travel purposes of home–shopping, home–escort and home–other are key to this result, which is also related to the transfer of the commute cost function. This further reinforces the recommendation of revisiting the model specifications for these journey purposes in any future estimation work. For discretionary travel purposes the sensitivity to changes in IVT is also on the low side. Thus the predicted impact of policy interventions that result in cost and/or time changes may be somewhat lower than anticipated.

It is noted, however, that PT fare elasticities have historically been low for the previous LTS model, especially for commute and home–business purposes. This is because there are fewer destination and mode options for these journeys, given that the jobs are predominately located in Central and Inner London. Large shifts away from public transport are unrealistic for these journeys.

6.3. Tour and detour lengths

The ability of the models to replicate observed tour lengths by mode has been investigated, and comparisons have also been undertaken of observed and predicted tour length distributions summing data across all modes. These investigations have been undertaken for each journey purpose.

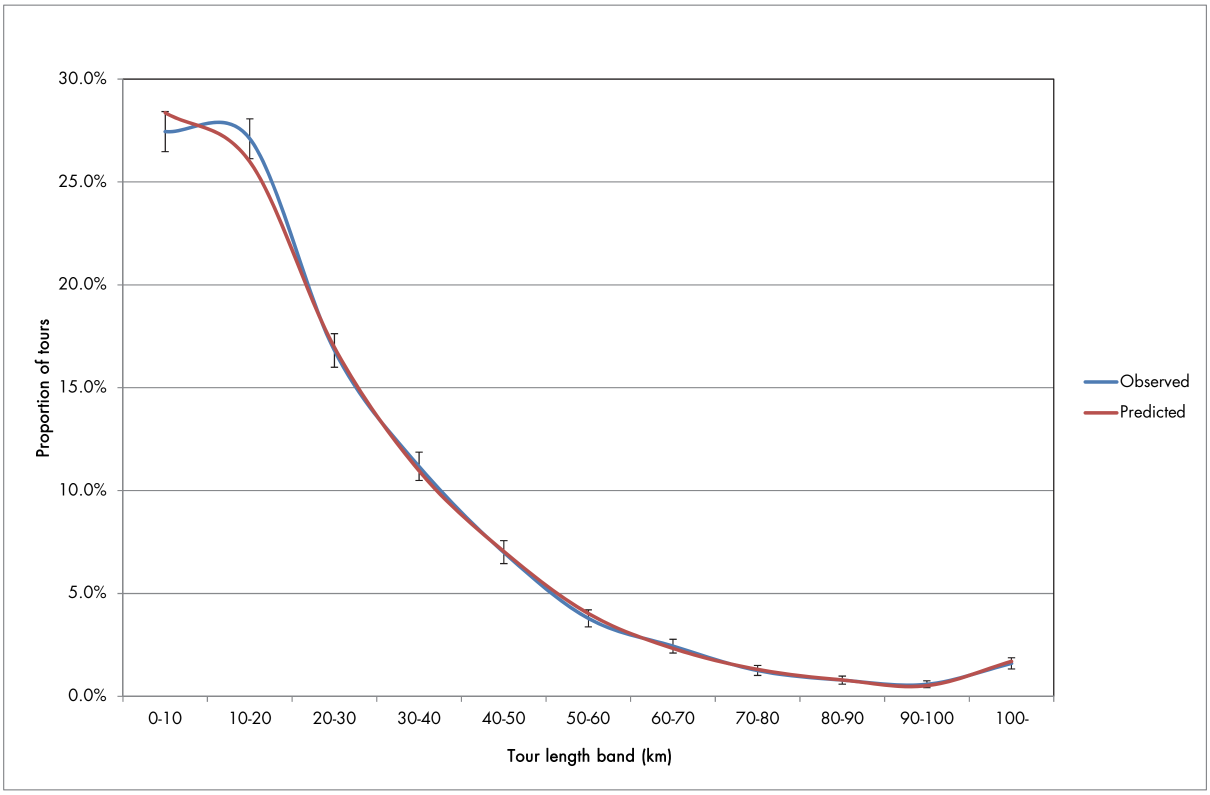
Consistent with model estimation, external destinations were only available in the tour length calculations for commute travel.

Table 29. Observed and predicted average commute tour lengths (km)

Mode	Sample	Observed tour lengths	Predicted tour lengths	Ratio
car driver	2,719	26.0	25.7	0.99
car passenger	283	21.1	20.9	0.99
rail	3,015	35.1	35.7	1.02
bus	1,138	13.5	14.2	1.06
taxi	27	15.0	11.2	0.75
cycle	359	14.4	14.4	1.01
walk	824	4.8	4.8	1.00
Total	8,365	24.8	25.0	1.01

For commute, observed and predicted tour lengths match well for all modes except taxi, which has a mode share of just 0.3 per cent.

Figure 16. Observed and predicted commute tour length distributions



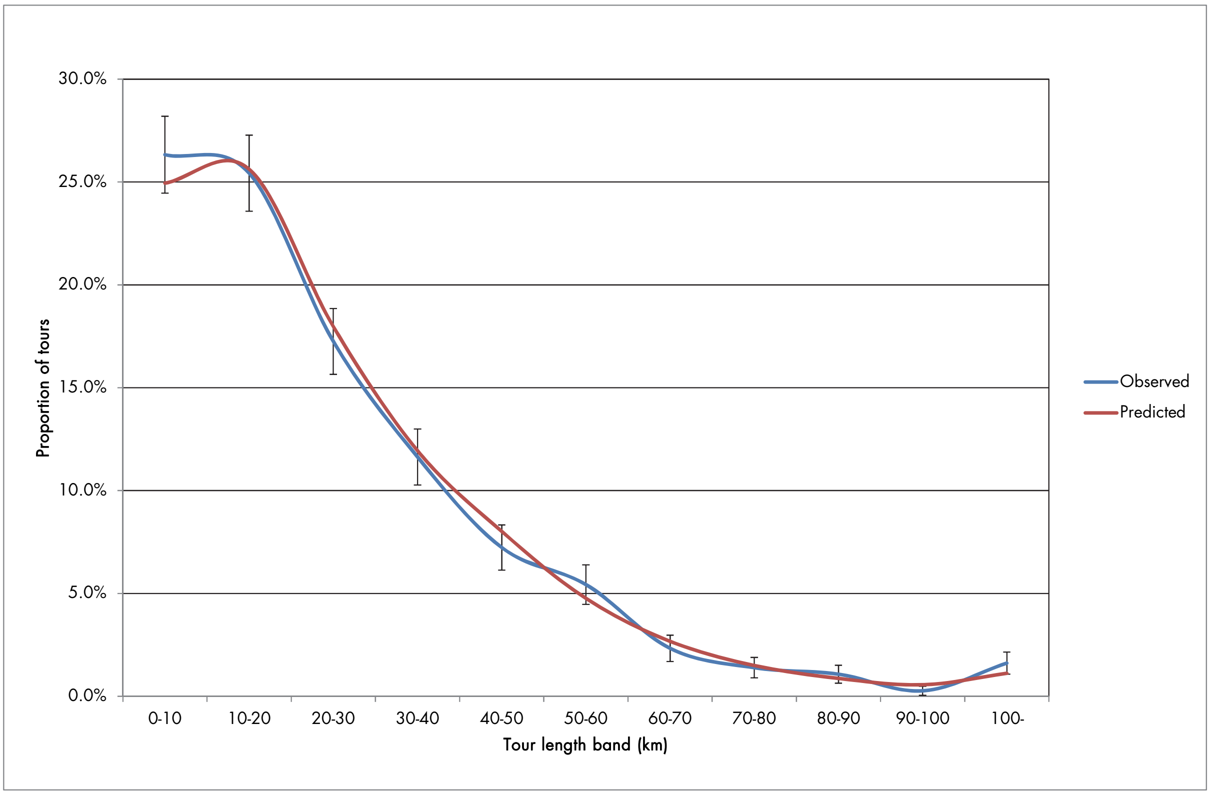
The observed tour length distribution is replicated well by the commute model across the full range of observed tour lengths.

Table 30. Observed and predicted average home–business tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car driver	918	25.4	26.6	1.05
car passenger	103	26.6	26.3	0.99
rail	652	35.0	34.5	0.99
bus	265	14.6	15.8	1.08
taxi	25	18.6	19.7	1.06
cycle	96	12.4	12.5	1.01
walk	149	4.6	4.7	1.01
Total	2,208	25.0	25.5	1.02

For business travel, the match between observed and predicted tour lengths is good for all modes except car passenger, where the model predicts a tour length closer to that observed for car driver rather than the high observed mean car passenger tour distance of 46.1 km. The high observed car passenger tour distance is likely to be biased upwards by a few long distance tours.

Figure 17. Observed and predicted home–business tour length distributions



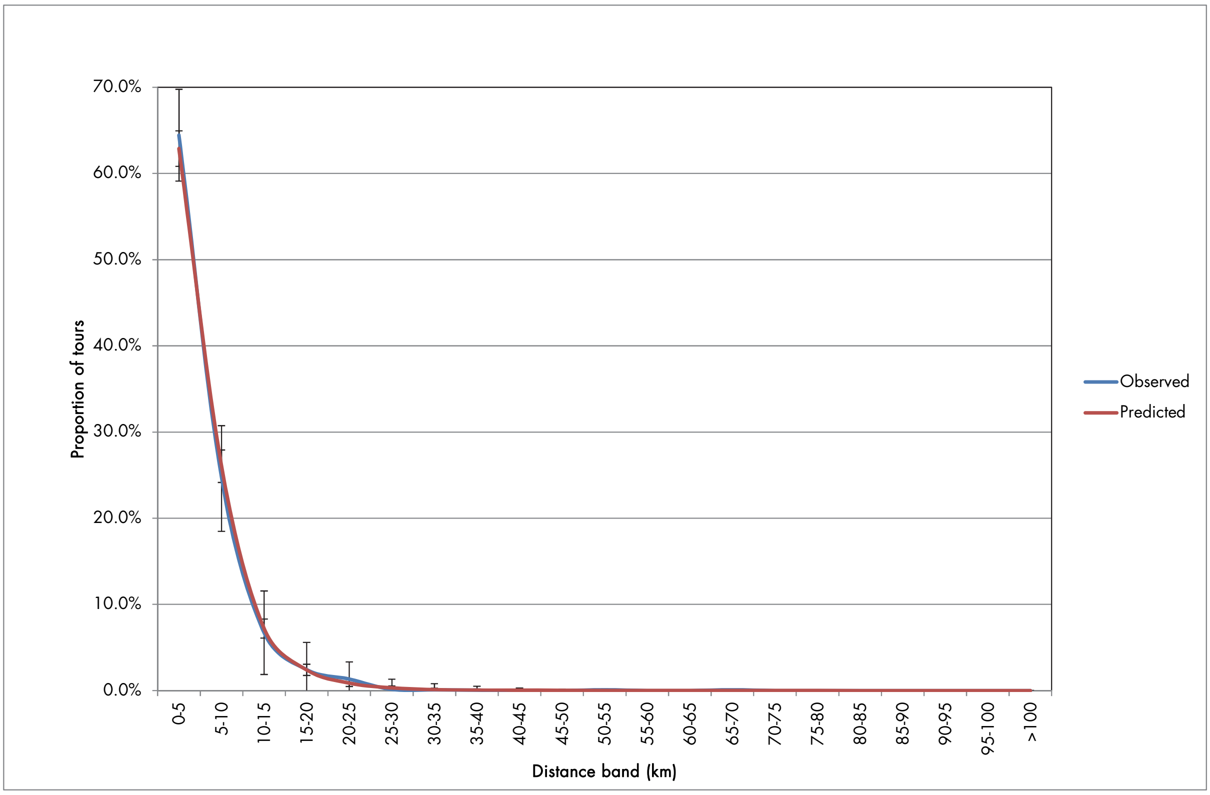
There is a slight under-prediction of tours in the 0–10 km band but overall the observed tour length distribution is replicated well by the model.

Table 31. Observed and predicted average home–primary education tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car passenger	668	7.4	7.3	0.99
rail	16	18.8	21.9	1.16
bus	263	8.3	8.7	1.05
taxi	2	10.0	12.0	1.20
cycle	42	3.8	4.0	1.04
walk	1,183	3.4	3.4	1.01
Total	2,174	5.3	5.4	1.02

For home–primary education travel, the observed and predicted tour lengths match well with observed tour distances, matching to within 5 per cent for all modes except rail and taxi. As can be seen from Table 31, the observed tour lengths for rail and taxi are based on small sample sizes.

Figure 18. Observed and predicted home–primary education tour length distributions



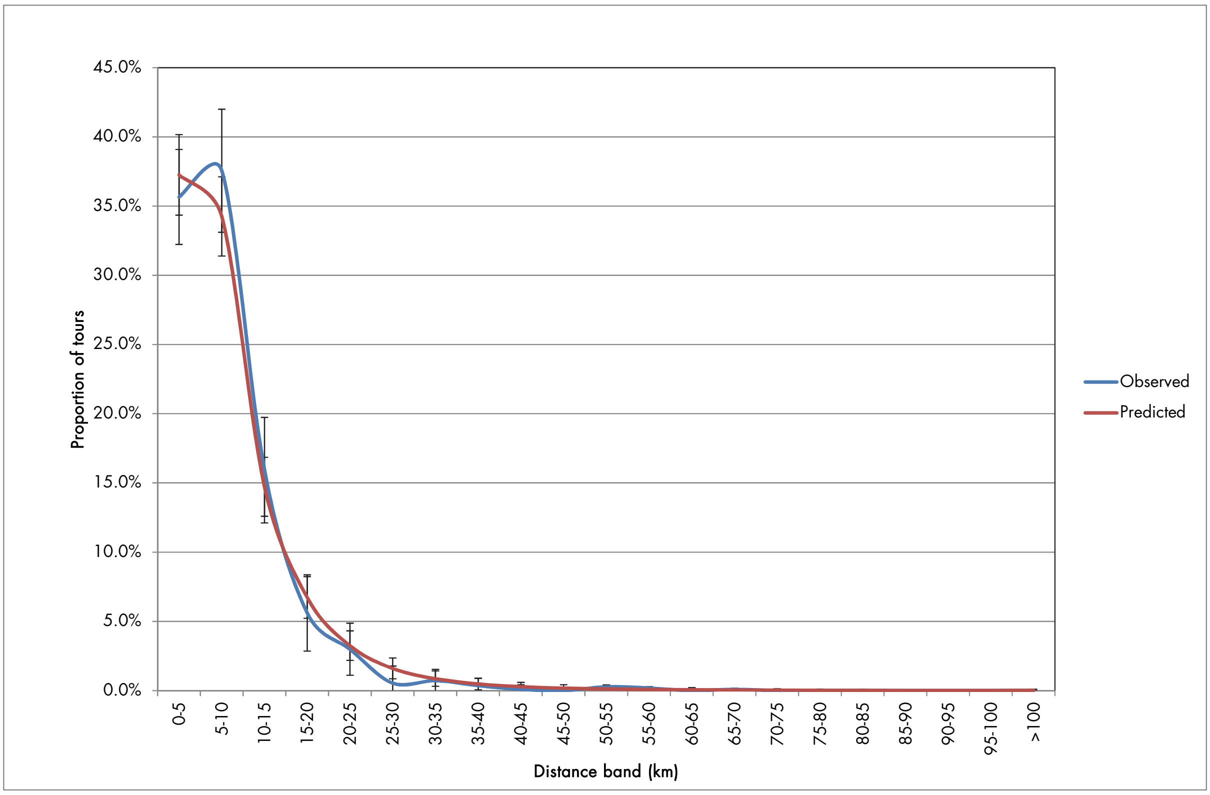
For primary education the predicted tour length distribution matches the observed distribution well.

Table 32. Observed and predicted average home–secondary education tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car passenger	184	9.2	9.3	1.00
rail	56	19.7	22.1	1.13
bus	490	9.8	10.3	1.05
taxi	4	16.9	24.3	1.44
cycle	12	4.4	5.1	1.16
walk	359	4.1	4.2	1.01
Total	1,105	8.3	8.7	1.05

For home–secondary education travel, tour distances are generally predicted well but some modes are over-predicted, in particular taxi, where the observed tour distance is based on just four observations.

Figure 19. Observed and predicted home–secondary education tour length distributions



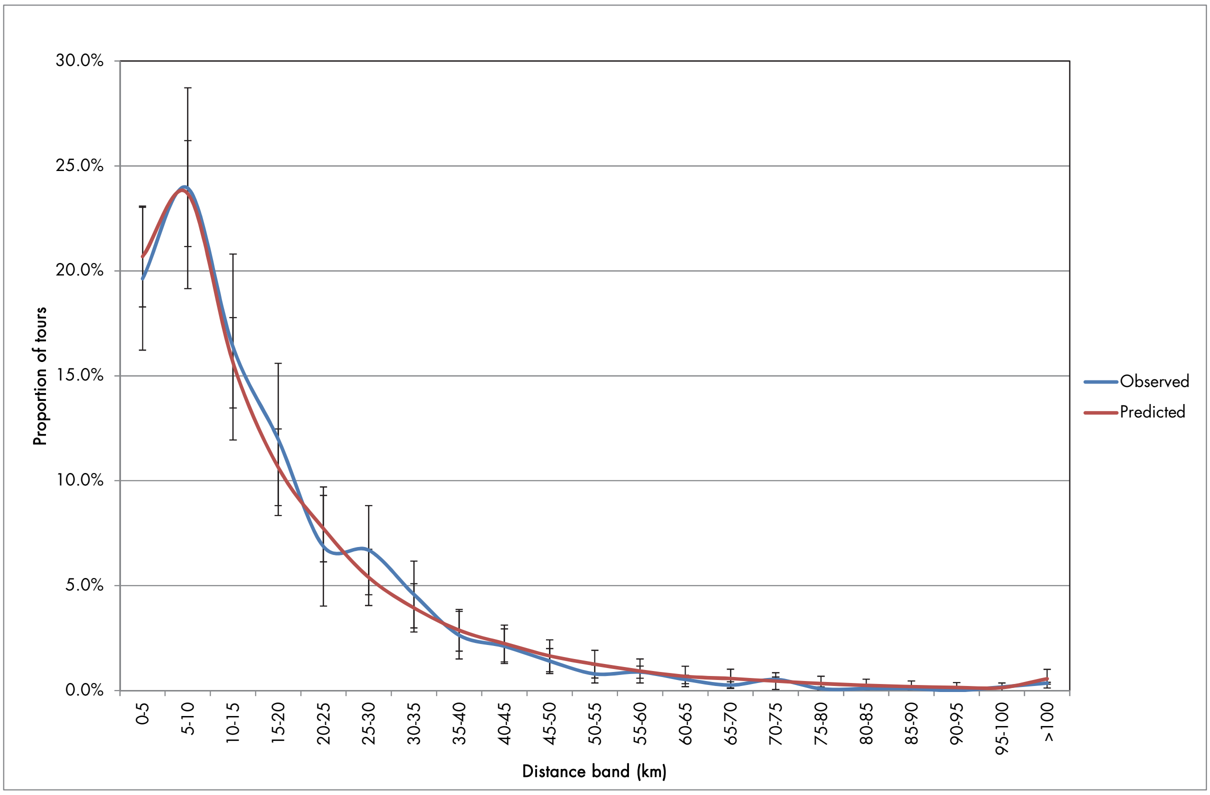
For home-secondary travel, there are some discrepancies between the observed and predicted tour length distributions for tours in the 0–5 km and 5–10 km bands, but otherwise there is a good correspondence between the observed and predicted distributions.

Table 33. Observed and predicted average home–tertiary education tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car driver	84	22.6	23.7	1.05
car passenger	59	15.9	15.7	0.99
rail	328	29.1	31.3	1.07
bus	375	13.1	13.2	1.00
taxi	5	14.9	14.0	0.94
cycle	40	12.4	12.5	1.00
walk	245	4.5	4.7	1.03
Total	1,136	16.7	17.5	1.04

For home–tertiary education travel, there is a reasonably good match between observed and predicted tour lengths for all modes, with all observed mean tour distances predicted to within ±10 per cent.

Figure 20. Observed and predicted home–tertiary education tour length distributions



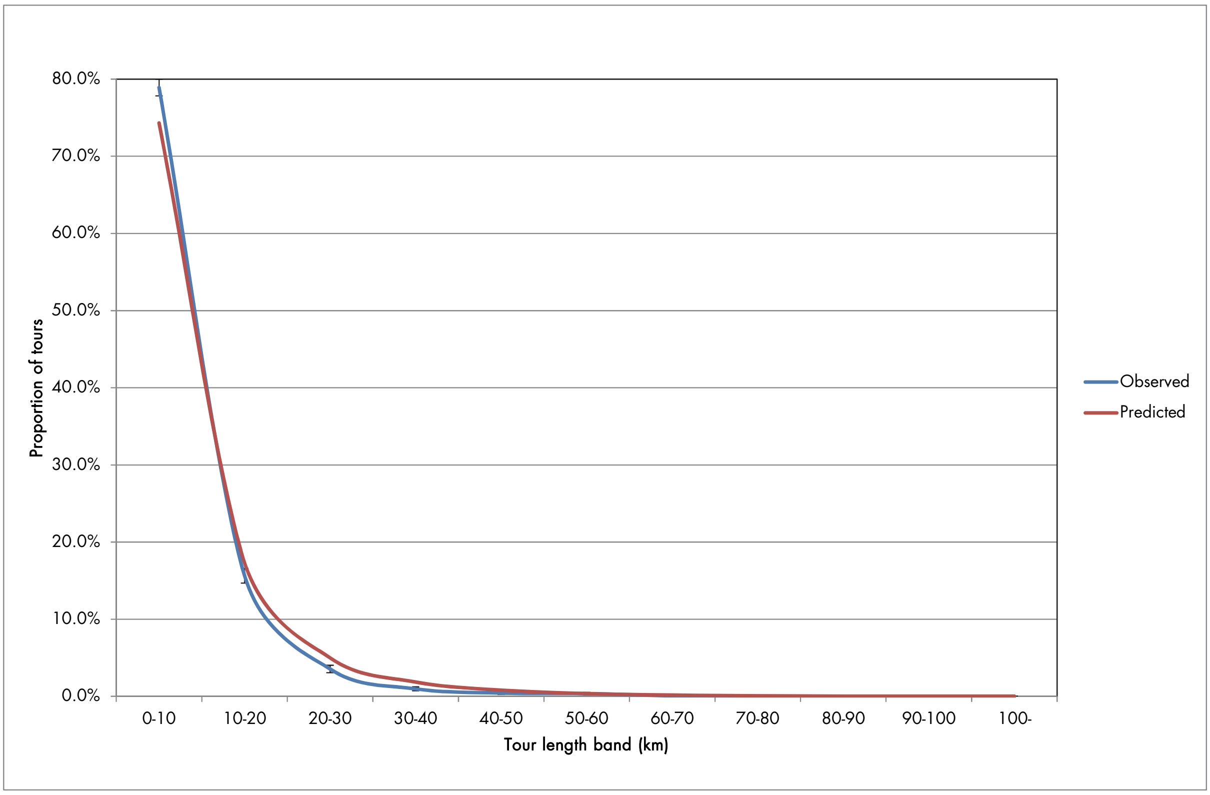
Over all modes, the shape of the lumpy observed tour length distribution is predicted well by the smoother predicted tour length distribution.

Table 34. Observed and predicted average home–shopping tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car driver	1,595	9.1	11.4	1.25
car passenger	572	10.9	13.8	1.27
rail	182	23.7	23.5	0.99
bus	1,134	8.8	9.0	1.03
taxi	13	6.8	5.4	0.79
cycle	85	4.8	5.1	1.05
walk	2,170	3.6	3.7	1.04
Total	5,751	7.5	8.6	1.14

For home–shopping, the tour lengths are predicted well for PT and active modes, but for car driver and car passenger, tour lengths are over-predicted by one-quarter and for taxi, tour lengths are under-predicted by one-fifth.

Figure 21. Observed and predicted home–shopping tour length distributions



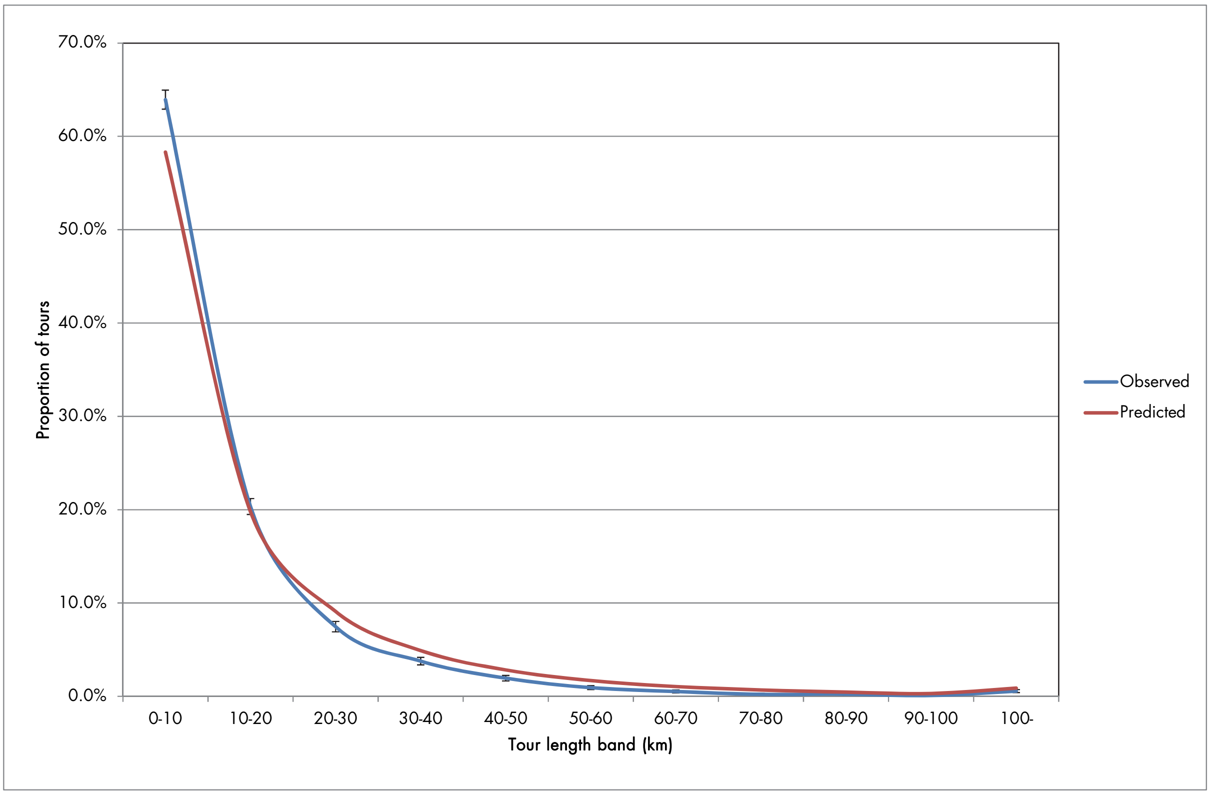
Overall, there is some under-prediction of the shortest tours in the 0–10 km band, and correspondingly some over-prediction of middle distance tours in the 20–30 km and 30–40 km bands.

Table 35. Observed and predicted average home–escort tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car driver	1,752	9.2	13.3	1.45
car passenger	99	14.5	28.7	1.98
rail	42	27.7	27.3	0.99
bus	188	8.3	9.7	1.17
taxi	12	41.9	6.0	0.14
cycle	28	3.9	4.2	1.08
walk	1,479	3.4	3.6	1.03
Total	3,600	7.2	9.7	1.35

The match between observed and predicted tour lengths is moderate for home–escort, with car driver tour lengths over-predicted by one half due to an under-prediction of the shortest trips. There is also a significant difference between observed and predicted taxi tour lengths.

Figure 22. Observed and predicted home–escort tour length distributions



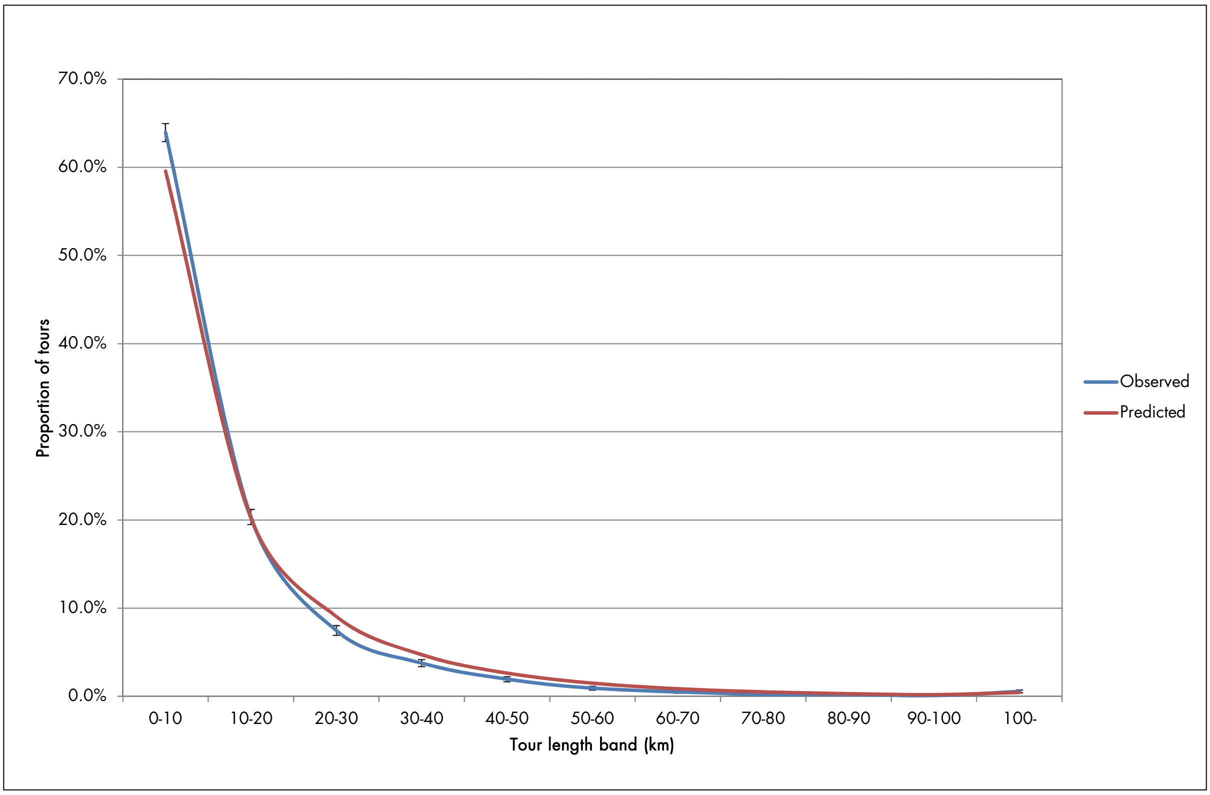
The overall shape of the observed distribution is replicated well, but as for shopping the shortest tours in the 0–10 km band are under-predicted and there is some over-prediction of middle distance tours.

Table 36. Observed and predicted average home–other travel tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car driver	2,435	12.8	16.3	1.27
car passenger	1,132	22.7	25.1	1.10
rail	766	29.5	30.0	1.02
bus	1,361	10.9	11.2	1.02
taxi	132	10.8	6.5	0.60
cycle	213	6.6	6.8	1.03
walk	2,787	3.9	4.0	1.02
Total	8,826	12.3	13.6	1.11

For home–other travel, the pattern is similar to that for home–escort, with car driver tour lengths over-predicted, taxi tour lengths under-predicted, and a better correspondence for other modes.

Figure 23. Observed and predicted home–other tour length distributions



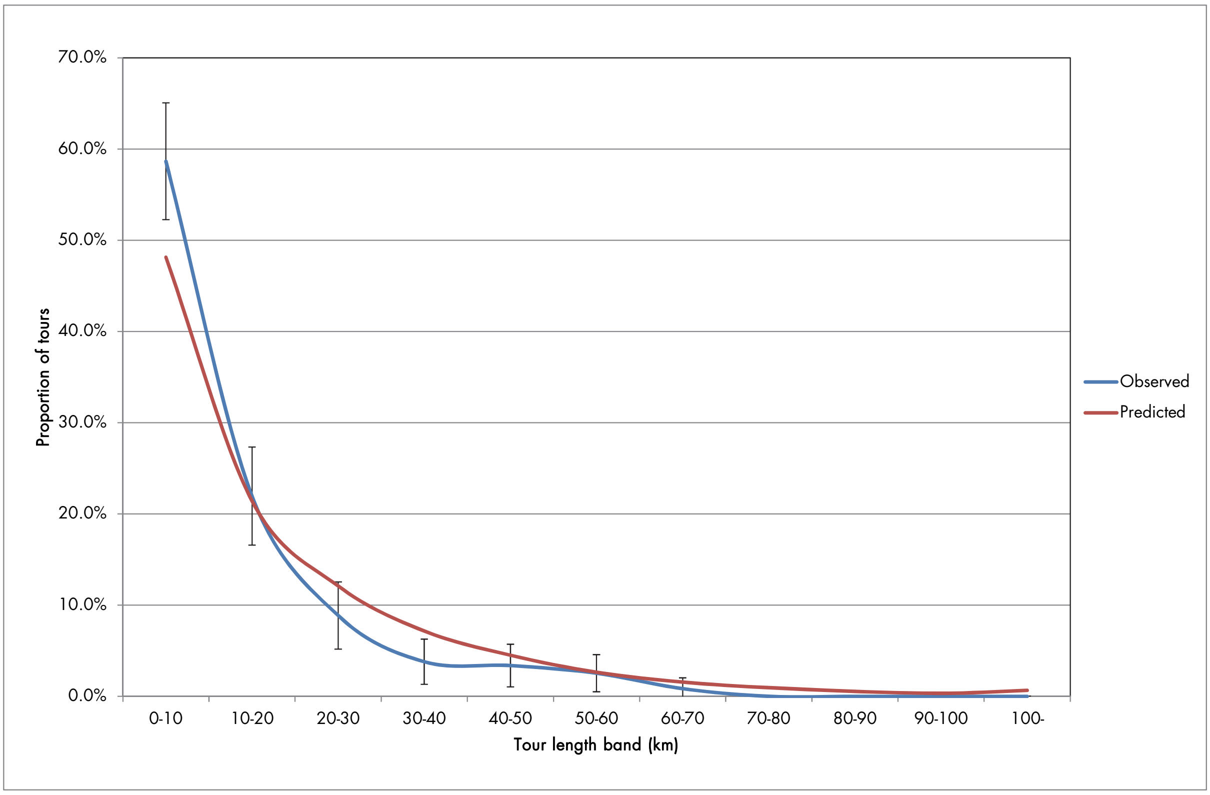
Overall the predicted distribution matches the shape of the observed distribution well, but consistent with shopping and escort the shortest tours are under-predicted and correspondingly there is some under-prediction of tours in the middle distance bands (20–30 km, 30–40 km, 40–50 km and 50–60 km).

Table 37. Observed and predicted average work–work tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car driver	89	15.7	27.6	1.76
car passenger	14	16.0	15.1	0.94
rail	59	17.9	18.7	1.05
bus	16	8.5	7.9	0.93
taxi	10	7.5	12.0	1.60
cycle	3	2.9	3.0	1.03
walk	46	3.3	3.6	1.08
Total	237	12.8	17.6	1.37

For NHB work–work tours, car driver and taxi tour lengths are significantly over-predicted, contributing to an overall over-prediction of 37 per cent. Tour lengths for the other modes are predicted to within ±10 per cent of the observed values.

Figure 24. Observed and predicted work–work tour length distributions



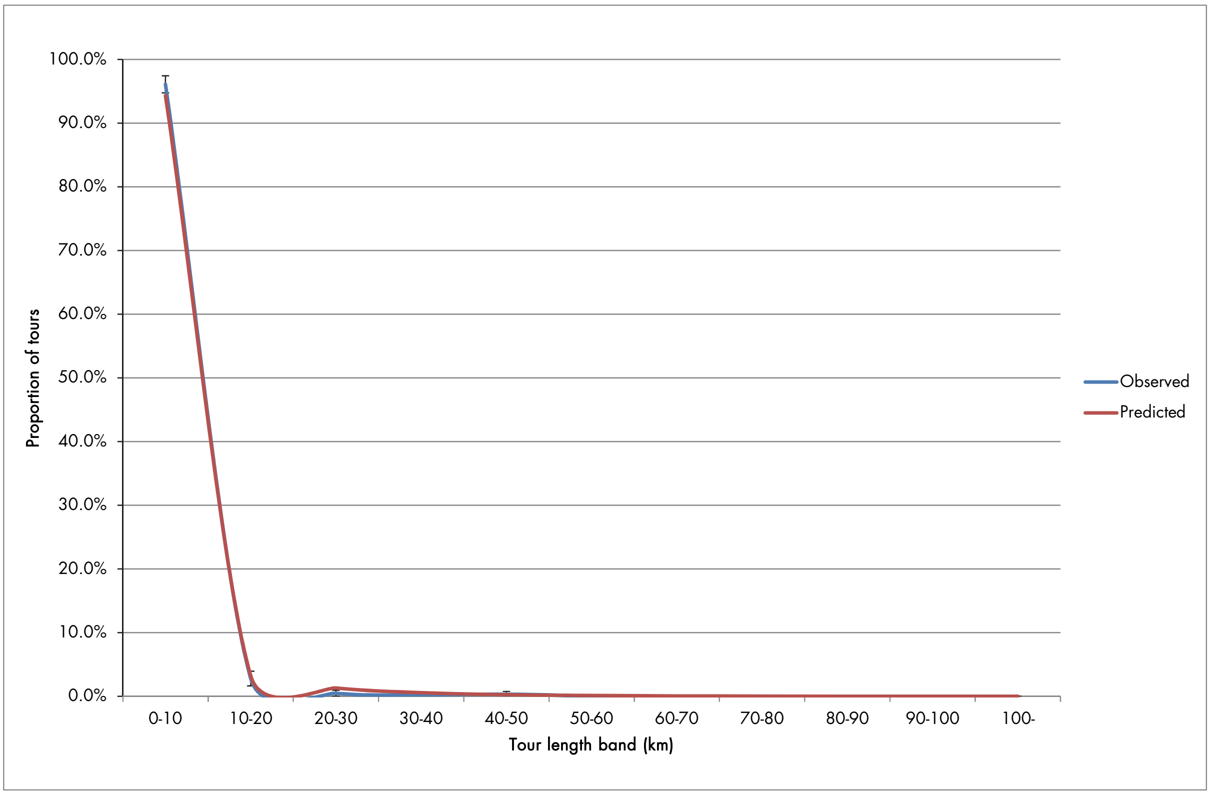
The shortest tours are under-predicted and, balancing that, middle and longer distance tours are over-predicted, with a significant difference between observed and predicted data in the 30–40 km band.

Table 38. Observed and predicted average work–other tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car driver	39	10.2	18.5	1.80
car passenger	2	11.1	17.3	1.56
rail	19	12.0	14.1	1.18
bus	16	7.6	8.9	1.17
taxi	6	13.4	15.6	1.16
cycle	7	3.3	3.3	1.01
walk	730	2.5	2.7	1.07
Total	819	3.3	4.0	1.20

There is a reasonable match between observed and predicted work–other tour lengths. Tour lengths for car driver and car passenger are significantly over-predicted. The other modes are also over-predicted but to a lesser extent, with an overall over-prediction of 20 per cent.

Figure 25. Observed and predicted work–other tour length distributions



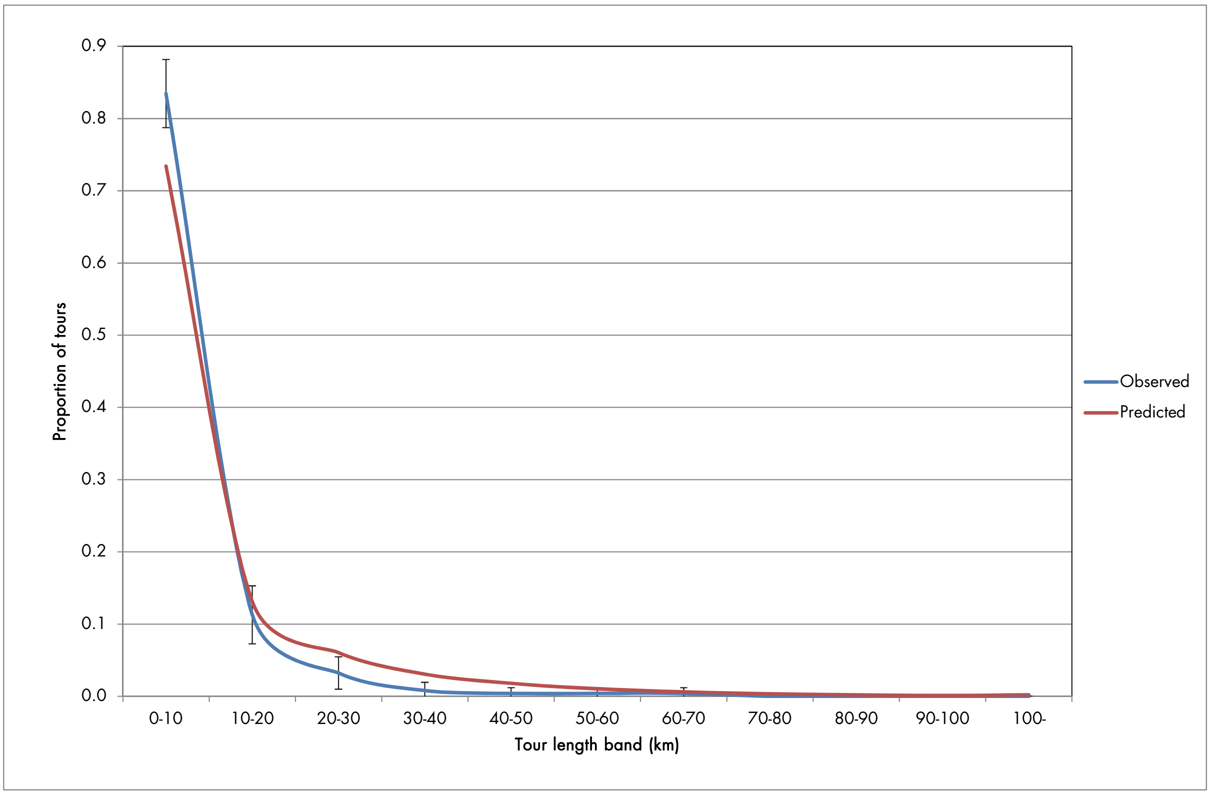
The short tour lengths for work–other tours means that most data are concentrated in the 0–10 km band.

Table 39. Observed and predicted average other–other tour lengths (km)

Mode	Sample	Observed tour length	Predicted tour length	Ratio
car driver	44	9.1	26.9	2.96
car passenger	22	8.3	8.1	0.98
rail	6	26.2	25.6	0.98
bus	37	11.0	12.0	1.09
taxi	2	28.9	25.6	0.89
cycle	2	4.2	3.5	0.85
walk	135	3.4	3.5	1.02
Total	248	6.8	10.0	1.48

For NHB other–other tour lengths, car driver tour lengths are significantly over-predicted. The predictions for the other modes are much better but the car driver over-prediction contributes to an overall over-prediction of 48 per cent.

Figure 26. Observed and predicted work–other tour length distributions



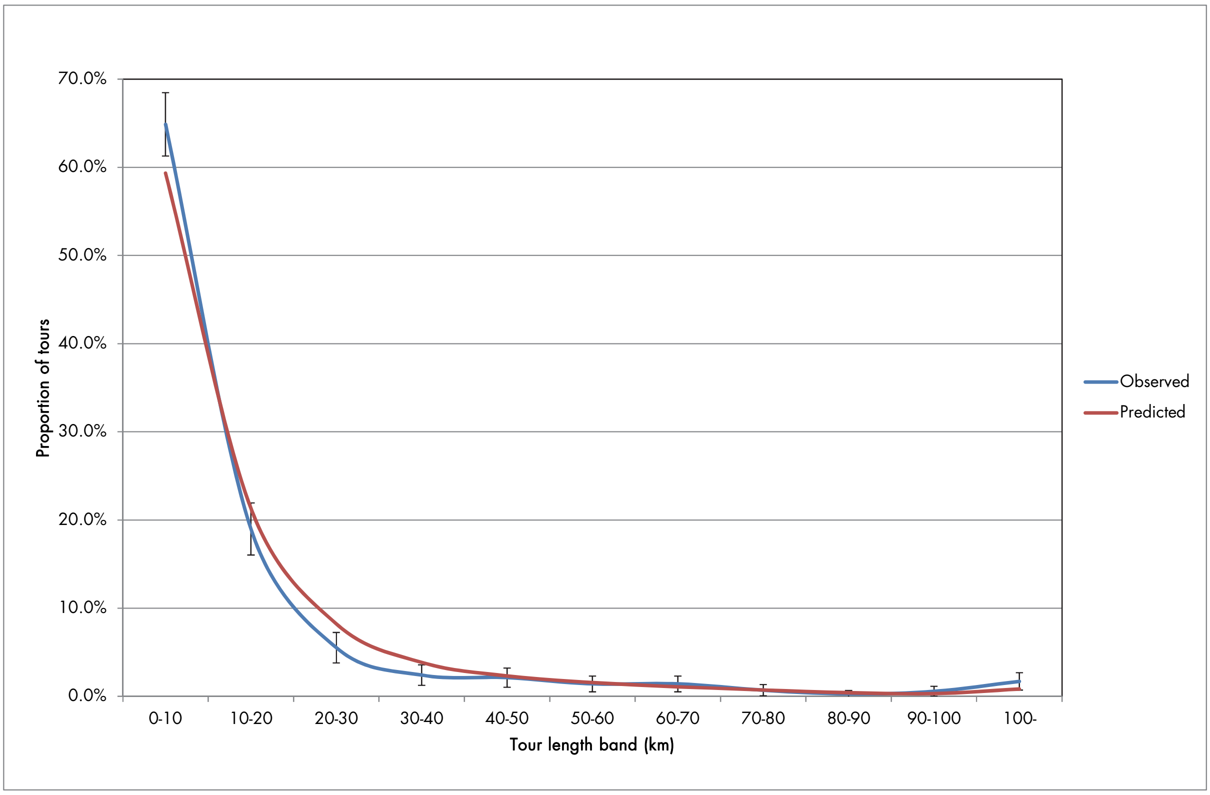
The shortest tours are under-predicted and, balancing that, tours in the 20–30 km, 20–30 km and 40–50 km bands are over-predicted.

Table 40. Observed and predicted average work–work detour lengths (km)

Mode	Sample	Observed detour length	Predicted detour length	Ratio
car driver	389	15.9	15.3	0.97
car passenger	32	19.8	22.1	1.11
rail	152	17.4	16.7	0.96
bus	60	5.4	5.1	0.94
taxi	13	6.0	7.8	1.30
cycle	19	3.8	4.6	1.23
walk	41	3.9	5.2	1.34
Total	706	14.3	14.1	0.99

Overall NHB work–work detour lengths are predicted accurately and, unlike the three NHB tour models, car driver tour lengths are predicted accurately. There is also a good match for PT modes. The worst fit is observed for taxi, but that accounts for just 13 observations.

Figure 27. Observed and predicted work–work detour length distributions



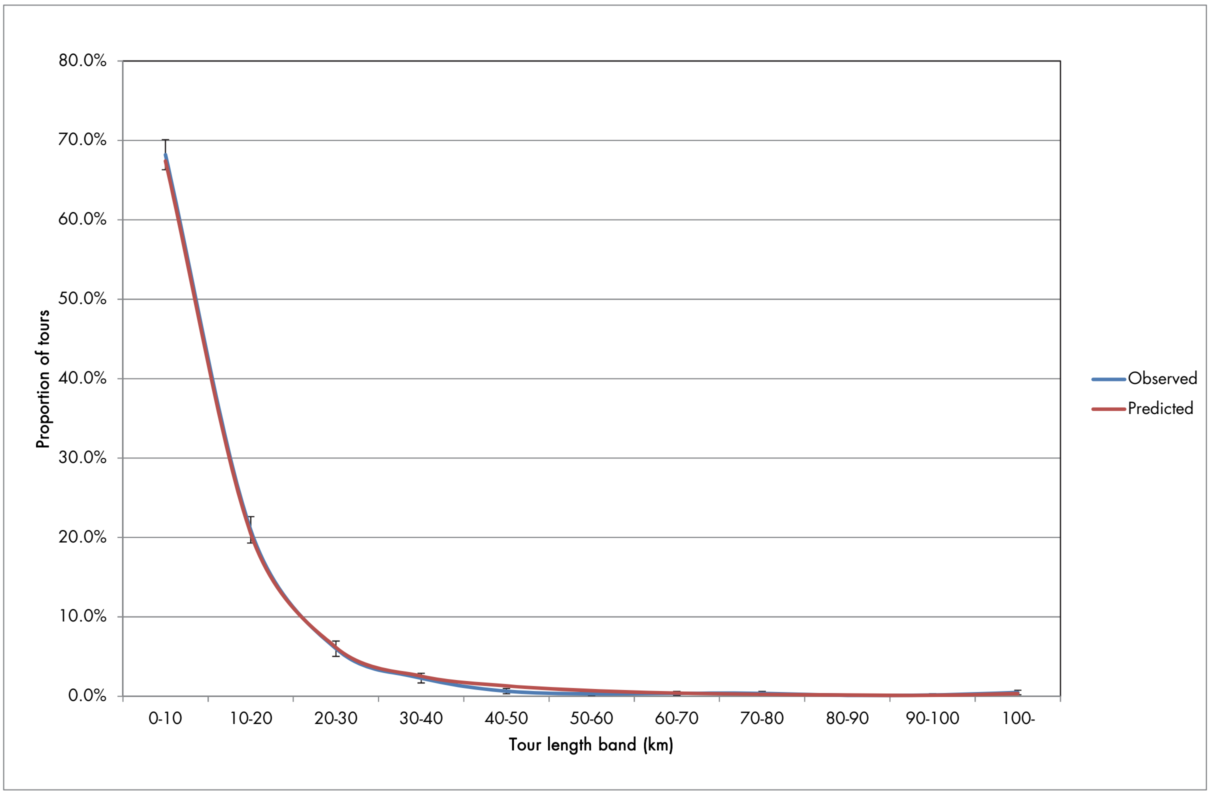
Once again the shortest tours are under-predicted and this is balanced by over-predictions for middle-distance bands. That said, the predicted distribution matches the shape of the observed reasonably well.

Table 41. Observed and predicted average work–other detour lengths (km)

Mode	Sample	Observed detour length	Predicted detour length	Ratio
car driver	1,034	11.8	11.8	1.00
car passenger	113	12.6	13.4	1.07
rail	464	13.7	16.5	1.21
bus	237	6.4	6.9	1.09
taxi	36	14.3	10.6	0.74
cycle	66	5.8	5.7	0.98
walk	482	3.9	3.9	1.00
Total	2,432	10.0	10.6	1.06

For NHB work–other detours, the rail detour length is significantly over-predicted and the taxi detour length is significantly under-predicted, but otherwise there is a good match between observed and predicted detour lengths.

Figure 28. Observed and predicted work–other detour length distributions



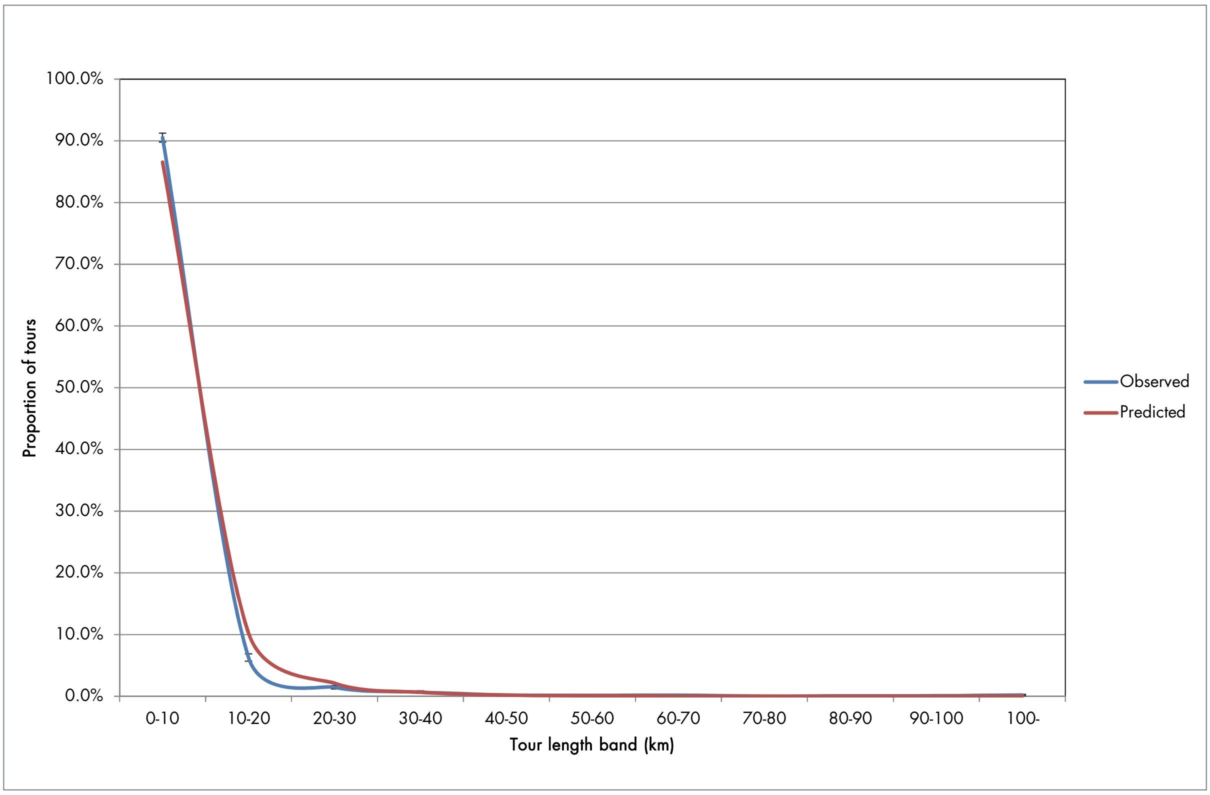
The predicted tour length distribution matches the observed distribution well across most tour length bands. However, there is a slight over-prediction of tours in the 40–50 km band.

Table 42. Observed and predicted average other–other detour lengths (km)

Mode	Sample	Observed detour length	Predicted detour length	Ratio
car driver	1,835	7.4	7.6	1.02
car passenger	1,017	7.3	7.5	1.03
rail	286	10.7	12.8	1.20
bus	808	4.4	5.4	1.22
taxi	37	8.4	7.1	0.84
cycle	68	2.6	3.4	1.30
walk	2,614	1.8	2.0	1.11
Total	4,830	4.9	5.4	1.09

For NHB other–other detours, detour lengths are predicted well for car driver and car passenger. There is some over-prediction for PT modes, cycle and walk, whereas taxi modes are under-predicted.

Figure 29. Observed and predicted other–other detour length distributions



Overall the observed and predicted tour length distributions match well. Consistent with a number of the other NHB purposes there is some under-prediction of the shortest tours.

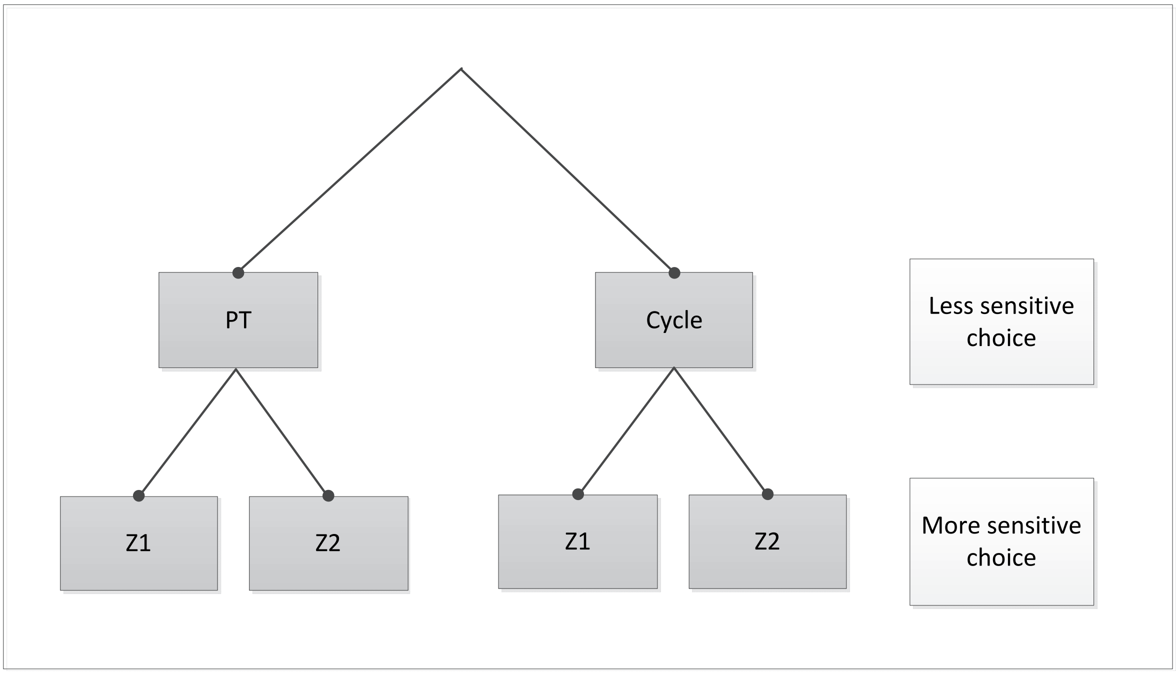
7. Cross-nested logit models

7.1. Motivation and simple example

The original intention of this project was to develop cross-nested logit (CNL) models that would better reflect mode-destination substitution patterns compared to nested logit (NL) models. In a modes-above-destinations NL structure, destinations are nested together reflecting greater substitution between destinations than between modes. However, if a particular mode-destination alternative in an NL structure is improved, demand is drawn from other modes equally over available destination alternatives and this substitution pattern can give rise to counter-intuitive results.

For example, consider a simple case for an individual in zone 1 choosing between PT and cycle and between destination zones 1 and 2. The example mode-destination nesting structure is given in Figure 30.

Figure 30. Nested logit example structure



Source: based on Jacobs (2017).

If there is a reduction in the cost of travel by cycle from zone 1 to 2, for example due to the construction of a cycle path, then the result of this for a NL structure with modes above destinations would be:

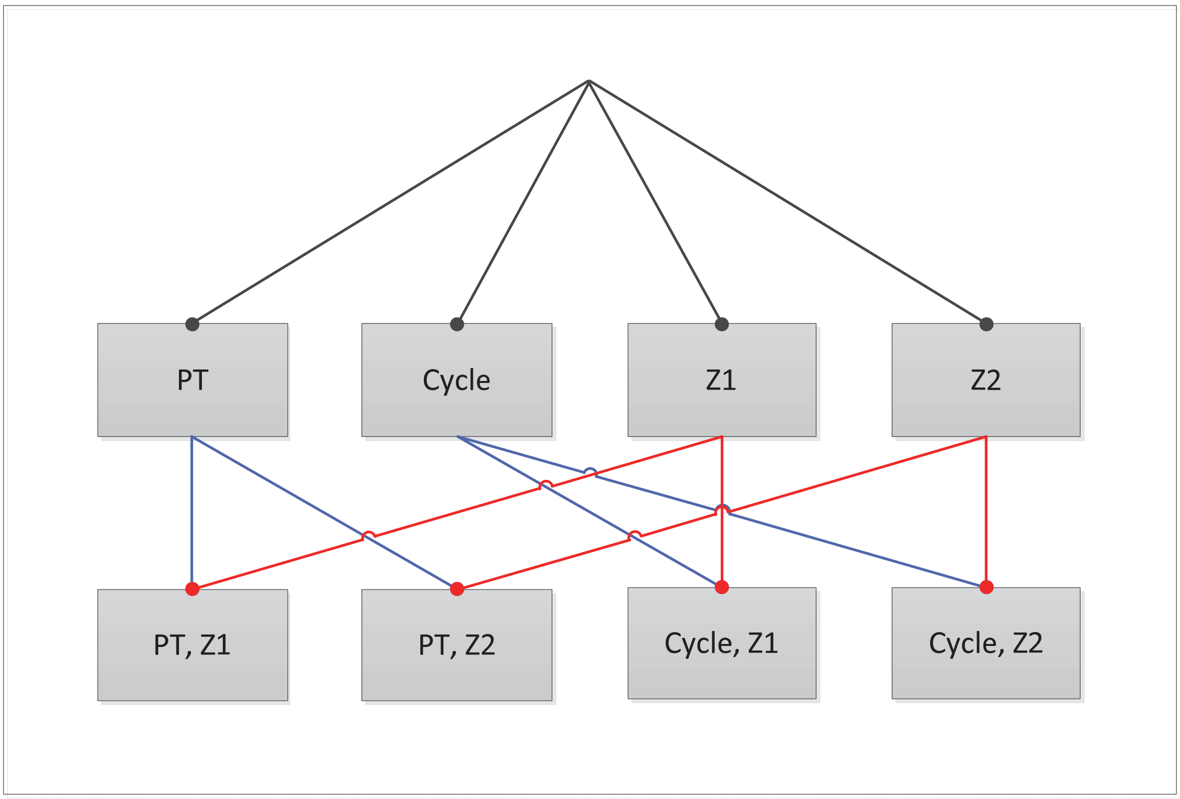
- An increase in cycle trips from zone 1 to zone 2
- A reduction in cycle trips from zone 1 to zone 1
- An overall increase in cycle trips
- An overall decrease in PT trips, applied uniformly to trips to zone 1 and zone 2.

The uniform reduction in PT trips to zones 1 and 2 is the property of the NL structure that cross-nested logit (CNL) seeks to improve upon, since it might reasonably be expected that the reduction in PT trips would be greater to zone 2 than to zone 1, or in other words that there is a correlation between choices appearing in two different nests (PT zone 2 and cycle zone 2). This distinction cannot be made with the NL models described in the previous chapters.

Conversely, if a tree structure was implemented with destinations above modes (although this is not observed in the data), this would have the effect for the scenario tested that there would be an overall decrease in trips to zone 1, applied uniformly across the modes. However, it would be expected that more cycle trips than PT trips would be diverted to zone 2. Thus, neither of the NL models represents the required effects fully.

Under the CNL formulation, however, alternatives can be part of more than one nest, and allocation parameters are used to control the extent to which an alternative lies in a particular nest. Returning to the simple PT and cycle example, the following CNL model can be specified.

Figure 31. Cross-nested logit example structure



In this example there are nests of destinations shown by the blue lines and nests of modes represented by the red lines. The reduction in the cost of travel to cycle to zone 2 would result in a decrease in PT trips with a greater reduction to zone 2 because of the operation of the Z2 mode nest, *and* a decrease in Z1 trips, with a greater reduction in cycle trips than in PT trips. Thus the CNL structure overcomes the issue of equal substitution from destinations for PT that is a feature of the NL (modes above destinations) substitution patterns, without introducing the opposite problem that would be a feature of the destinations above modes NL structure.

To specify a CNL model, a more detailed model specification is required with 'allocation parameters' that determine how much a particular mode and destination combination is allocated to its mode nest and how much is allocated to its destination nest. These can be viewed as weights that indicate how the probabilities from the mode nest and destination nests should be combined, with the weights summing to one. Additionally, the structural parameters may well be different from those appearing in the NL model.

7.2. Mathematical formulation

The general two-level cross-nested model gives the probability of alternative j (for a specific origin, purpose and person type) by:

$$p_j = \sum_n \frac{\left(\sum_k (\alpha_{kn} e^{V_k})^{1/\lambda_n}\right)^{\lambda_n}}{\sum_l \left(\sum_k (\alpha_{kl} e^{V_k})^{1/\lambda_l}\right)^{\lambda_l}} \frac{\left(\alpha_{jn} e^{V_j}\right)^{1/\lambda_n}}{\sum_k (\alpha_{kn} e^{V_k})^{1/\lambda_n}}, \text{ with } \alpha_{jn} \geq 0 \text{ and } \sum_n \alpha_{jn} = 1 \text{ for all } j \text{ and } n \qquad (7.1)$$

where α and λ are to be estimated and

V_j is the utility of alternative j

Note that this formulation gives the possibility that any alternative can be included in any nest, with $\alpha_{jn} = 0$ when j is not included in n. This is a fully general CNL specification, not specific to any particular application, such as transport modelling.

Note also that this is a normalised (RU2) specification with 'top-down' normalisation. The RU2 specification implies that the units are consistent at every level in the model, while top-down means that the scale is specified by the upper level in the model. Both of these features are different from ALOGIT, which we used to obtain the initial NL models, which are the starting points for the CNL work. Practically, this means that:

- V in ALOGIT corresponds to V/λ in this CNL specification, i.e. the ALOGIT estimated coefficients need to be multiplied by λ to use in CNL
- The hierarchy coefficient, usually called θ in ALOGIT, corresponds to λ in CNL
- The constraint $0 < \theta \leq 1$ in ALOGIT corresponds to $0 < \lambda \leq 1$ in CNL.

The notation θ will be used instead of λ because it is more familiar in transport analysis.

Finally, note that the first denominator in the model, i.e. $\sum_l \left(\sum_k (\alpha_{kl} e^{V_k})^{1/\theta_l}\right)^{\theta_l}$, represents the exponential of overall utility, so that the log of this can be used in other applications, e.g. in a higher-level model.

For the present model, the general specification (7.1) can be simplified; we have mode-destination alternatives and attach each alternative to the relevant mode and destination nests, so that the probability of each alternative is a sum over just two nests. We can then utilise the α parameters economically, so that:

> α_{dm} gives the allocation of the mode-destination alternative md to its mode nest m and
>
> α_{md} gives the allocation of the mode-destination alternative md to its destination nest d.

While this notation is somewhat abbreviated, it is concise and not misleading if used carefully. If further cross-nesting is introduced into the model (e.g. in the second option discussed in Section 7.3 below), the notation would in any case need to be revised. The αs must be non-negative and $\alpha_{md} + \alpha_{dm} = 1$.

The model then gives the probability of mode j and destination z by:

$$p_{jz} = \frac{\left(\sum_d \left(\alpha_{dj} e^{V_{jd}}\right)^{1/\theta_j}\right)^{\theta_j}}{\Omega_D + \Omega_M} \frac{\left(\alpha_{zj} e^{V_{jz}}\right)^{1/\theta_j}}{\sum_d \left(\alpha_{dj} e^{V_{jd}}\right)^{1/\theta_j}} + \frac{\left(\sum_m (\alpha_{mz} e^{V_{mz}})^{1/\theta_z}\right)^{\theta_z}}{\Omega_D + \Omega_M} \frac{\left(\alpha_{jz} e^{V_{jz}}\right)^{1/\theta_z}}{\sum_m (\alpha_{mz} e^{V_{mz}})^{1/\theta}} \tag{7.2}$$

In this model the overall exponentiated utility is given by the sum of exponentiated utility over both mode and destination nests, i.e.:

$$\Omega_M = \sum_m \left(\sum_d (\alpha_{dm} e^{V_{md}})^{1/\theta_m}\right)^{\theta_m} \text{ and } \Omega_D = \sum_d \left(\sum_m (\alpha_{md} e^{V_{md}})^{1/\theta_d}\right)^{\theta_d} \tag{7.3}$$

It seems reasonable to consider the possibility that the allocation parameters do not depend on the specific modes and destinations, i.e. $\alpha_{dm} = \alpha_M$ and $\alpha_{md} = \alpha_D$ for all m and d, with of course $\alpha_M + \alpha_D = 1$. This allows the simplification:

$$p_{jz} = \frac{\alpha_M \left(\sum_d \left(e^{V_{jd}}\right)^{1/\theta}\right)^{\theta_j}}{\Omega_D + \Omega_M} \frac{\left(e^{V_{jz}}\right)^{1/\theta_j}}{\sum_d \left(e^{V_{jd}}\right)^{1/\theta_j}} + \frac{\alpha_D \left(\sum_m (e^{V_{mz}})^{1/\theta_z}\right)^{\theta_z}}{\Omega_D + \Omega_M} \frac{\left(e^{V_{jz}}\right)^{1/\theta_z}}{\sum_m (e^{V_{mz}})^{1/\theta_z}} \tag{7.4}$$

$$\Omega_M = \alpha_M \sum_m \left(\sum_d (e^{V_{md}})^{1/\theta_m}\right)^{\theta_m} \text{ and } \Omega_D = \alpha_D \sum_d \left(\sum_m (e^{V_{md}})^{1/\theta}\right)^{\theta_d} \tag{7.5}$$

or, perhaps more concisely:

$$p_{jz} = \alpha_M \frac{\left(\sum_d \exp^{V_{jd}}/_{\theta_j}\right)^{\theta_j}}{\Omega_D + \Omega_M} \frac{\exp^{V_{jz}}/_{\theta_j}}{\sum_d \exp^{V_{jd}}/_{\theta_j}} + \alpha_D \frac{\left(\sum_m \exp^{V_{mz}}/_{\theta_z}\right)^{\theta_z}}{\Omega_D + \Omega_M} \frac{\exp^{V_{jz}}/_{\theta_z}}{\sum_m \exp^{V_{mz}}/_{\theta_z}} \tag{7.6}$$

$$\Omega_M = \alpha_M \sum_m \left(\sum_d \exp^{V_{md}}/_{\theta_m}\right)^{\theta_m} \text{ and } \Omega_D = \alpha_D \sum_d \left(\sum_m \exp^{V_{md}}/_{\theta_d}\right)^{\theta_d} \tag{7.7}$$

It would also be reasonable to assume some equalities among the θs, in particular that the model scale within each destination nest was constant, i.e. $\theta_d = \theta_D$ for all d. However, this does not simplify the equations significantly.

The validity of the formulae and the fact that the CNL generalises tree-nested models can be checked by seeing that if $\alpha_D = 0$ we obtain a standard tree-nested model with modes 'above' destinations; conversely, if $\alpha_M = 0$ we get a tree-nested model with destinations above modes. Only when both αs are positive do we get cross-nesting. When $\alpha_D = 0$ the θ_z parameters vanish from the model and when $\alpha_M = 0$ the θ_m parameters vanish.

7.3. Model results

CNL models have been estimated for two purposes: commute and other travel. The model estimation procedure used a grid search approach, in which pre-specified values for the CNL parameters were tested. Five parameters were varied in the grid-search:

- α_M and α_D, the CNL allocation parameters
- θ_M and θ_D, the mode and destination nesting parameters
- The overall model scale.

Throughout the testing, the values of the other parameters were held fixed to the values estimated in the NL models described in previous chapters.

It is noted that the need to vary parameters across five dimensions complicates the grid search and makes it difficult to present model results clearly because of the number of dimensions. The key metric used for the model results was fit to the mode-destination choices observed in the LTDS data, which can be compared to the fit obtained in the best NL structure. Fit is measured by the log-likelihood.[16]

The first stage in the CNL grid search was to run a check that the model was able to replicate the log-likelihood of the two NL structures that provide limits to the grid search procedure, modes above destinations and destinations above modes. That check was satisfactory for both of the NL structures for both commute and other travel. Then the grid search for CNL model parameters that gave an improved fit to the data commenced.

The NL model parameters that are used to calculate the utility of each mode-destination alternative were held fixed in the grid search. Figure 32 illustrates how the grid search worked for commute, demonstrating how it moved from the centre of the search space to the top right of the graph based on the model results, i.e. to fit to the observed mode-destination choices in the LTDS data. The best results were obtained for α_M values of 1, i.e. the same as the NL model results with modes above destinations.

[16] Likelihood is measured by the probability of the observed choices for all of the data. It is more convenient to work with the logarithm of the probabilities.

Figure 32. Illustration of grid search process for commute CNL runs

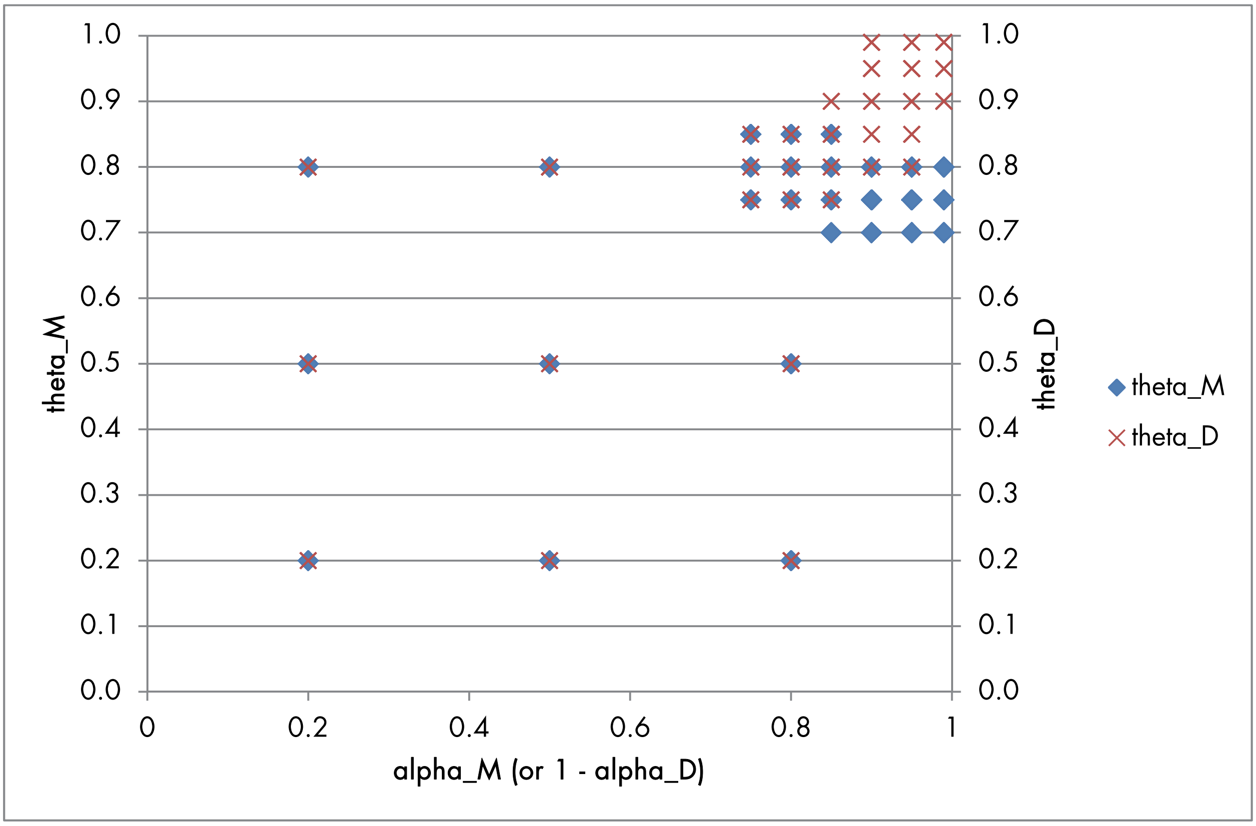


Figure 33 illustrates the results from the grid-search procedure for commute, plotting how the fit to the mode-destination choices observed in the LTDS data varies with different α_M and θ_M values. The variation in fit illustrated along the horizontal axis is for different values of α_D and θ_D, with fit measured relative to the best NL model. The corresponding plot in Figure 34 illustrates how the model fit varies with different α_D and θ_D values, with the variation in model fit shown on the x-axis a result of using different values of α_M and θ_M.

Figure 33. Commute CNL tests, variation in fit with α_M and θ_M

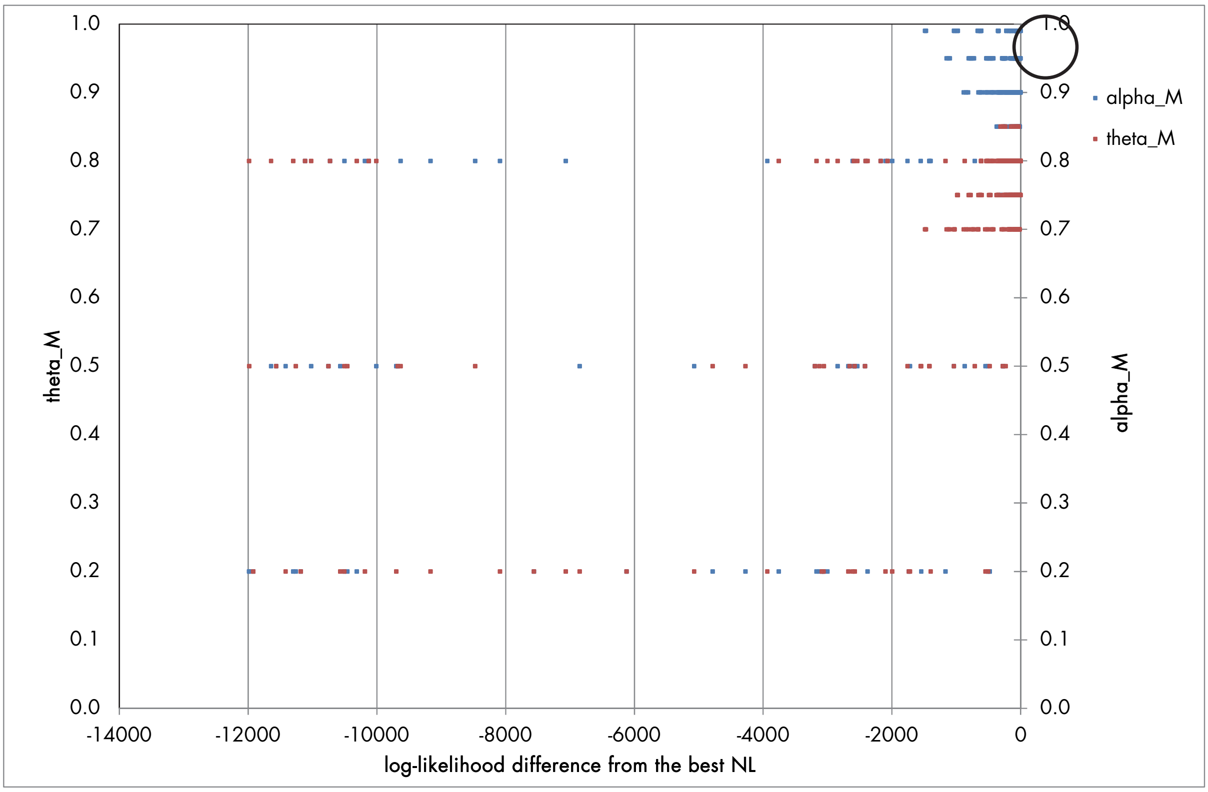
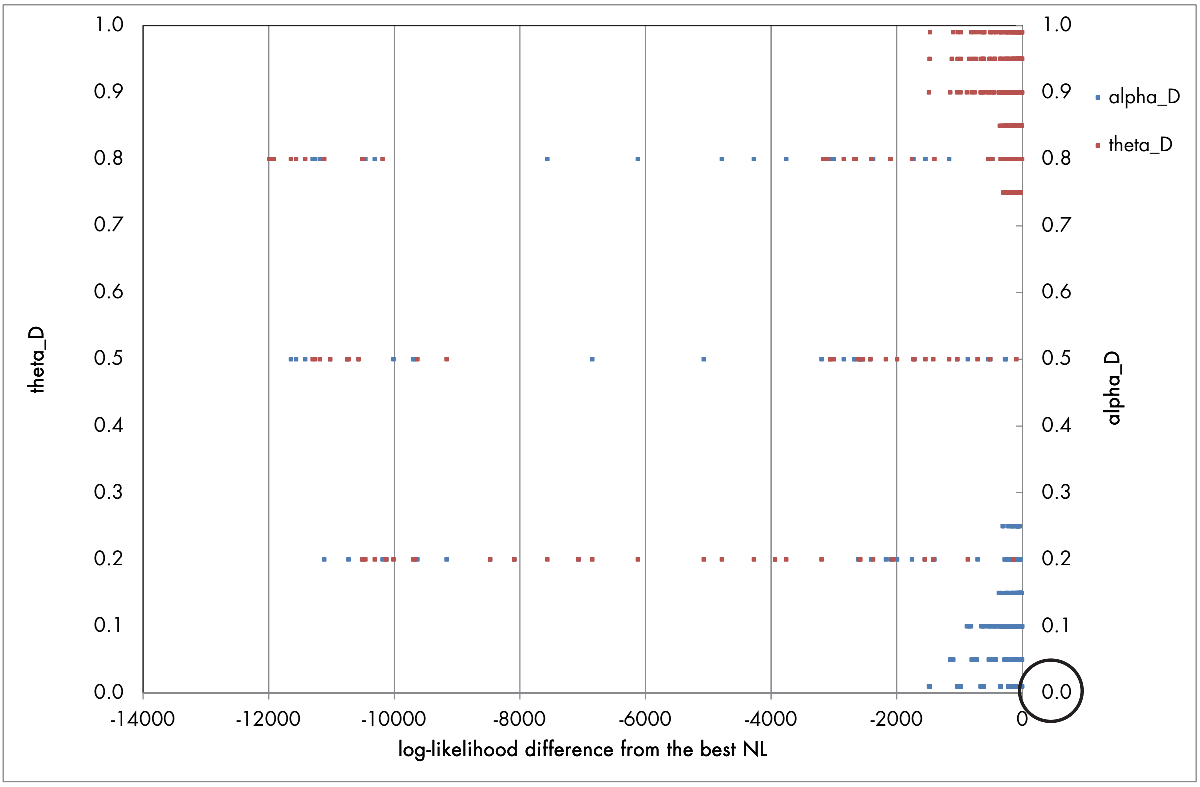


Figure 34. Commute CNL tests, variation in fit with α_D and θ_D



It can be seen that no values have been identified in the grid search that give any improvement in fit to the data relative to the modes above destinations structure, the $\alpha_M = 1$ and $\alpha_D = 0$ result highlighted in the two graphs. Not shown in Figure 34 is the searching that was done for different values of model scale. However, once again, the best values were found to be indistinguishable from the NL value.

Some testing was initiated to understand why the log-likelihood of the CNL models was worse than that of the NL models. Runs were undertaken where mode constants were re-estimated in the CNL models to match the observed mode shares. These runs recovered some of the loss of likelihood relative to the NL model results, but the results still remained worse than the NL. The option of fully re-estimating all of the model parameters in the CNL context was not possible within the grid-search approach adopted for this study. This would require efficient software for large-scale CNL estimation and such software is not readily available, to the best of our knowledge.

For home–other, the picture was different. The grid search did uncover CNL results that gave some improvement in model fit relative to the NL models, but these CNL models were very close to the simpler NL models. Table 1 presents first the NL results, then the results from three models termed CNL 1 to CNL 3 are presented, showing the maximum improvements in fit relative to the NL model. The final model presented, CNL 4, was identified by the grid search and replicates the NL log-likelihood exactly.

Table 43. Other CNL tests, best grid search results

Run	α_M	α_D	θ_M	θ_D	scale	model fit	diff in fit from NL
NL	1	0	0.3205	n/a	0.3205	-47,360.0	0.0
CNL 1	0.999	0.001	0.31	0.9	0.33	-47,180.0	180.0
CNL 2	0.999	0.001	0.31	0.8	0.33	-47,188.3	171.7
CNL 3	0.999	0.001	0.31	0.9	0.3205	-47,190.1	169.9
CNL 4	1	0	0.3205	n/a	0.3205	-47,360.0	0.0

It can be seen that the best CNL model results are for α_M values very close to 1, such that in practical terms the substitution patterns in the model would be indistinguishable from those in the NL modes-above-destinations structure. Thus there would be no practical benefit to implementing the more complex CNL models. It had been hoped that α_M and α_D parameters further from 1 and 0 would be identified that would justify the use of CNL, but this did not transpire.

Overall it was concluded that it was not possible to identify CNL models that yielded a significant improvement in fit to the NL models using the grid-search approach and that were suitable for policy testing, and therefore the final models recommended for implementation are the best NL models. Our recommendation is that the best way forward it is investigate options for formally estimating the CNL models rather than employing a grid-search approach.

8. Summary and recommendations

NL models have been estimated for eight HB and six NHB purposes.

For commute and home–business, it was possible to estimate plausible cost functions reflecting variation in cost sensitivity with income band and journey cost. For home–shopping, home–escort and home–other travel, this was not possible and so the commute cost function was transferred. For home–tertiary education and for work–work detours, cost functions reflecting variation in cost sensitivity with journey cost have been estimated. For the other five of the six NHB purposes, VoTs were imported from WebTAG.

For non-business purposes, the models reflect cost sharing between car drivers and car passengers and so in policy testing predicted occupancy levels will be responsive to changes in car cost.

When separate crowding terms were estimated they were wrongly signed (positive) for all of the HB purposes, implying travellers prefer more crowded services. Therefore a number of model specification search tests were undertaken to determine the best representation for the PT LOS terms. For all but one of the HB purposes (home–escort was the exception) and for work–work detours, PT OVT and crowding were combined into a single term for which plausible negative estimates were obtained. For five of the six NHB purposes (i.e. all the NHB purposes except work–work detours), the PT OVT and crowding components were added to IVT, and sensitivities to generalised time by mode were estimated instead. One noticeable feature of the model results is that rail IVT sensitivities were consistently lower than those for car and bus, meaning that in application the models will be relatively insensitive to changes in rail IVT.

For all but one of the HB purposes (home–secondary education), the mode-destination model estimations were able to capture differences in preferences for cycling between low cycle propensity (LCP) and high cycle propensity (LCP) groups. In forecasting, moving a higher fraction of the population to the HCP group will result in increases in demand for cycling.

A wide range of segmentation effects has been identified in the HB model specifications. Segmentations by car availability, gender, age, employment status, occupation, pass ownership, disability, household income and household type are represented. For the NHB models, the sample sizes are smaller and so fewer segmentation terms have been identified. The most important segmentation terms in the NHB models are those capturing strong correlations between the NHB tour mode and the tour mode used for the associated HB tour.

A number of origin and destination effects have been identified in the models. These include employment density terms in both the commute and home–business models to capture higher rail use to high employment density areas such as Canary Wharf, and population density effects interacted on mode choice in the home–shopping and home–other travel models.

Structural tests were carried out to investigate the relative sensitivity of the different choices modelled. For commute, the best structure identified had main modes nested above simultaneous PT modes and destinations, reflecting higher cross-elasticities between PT modes than across PT and non-PT modes relative to a structure where PT modes are represented at the same level as other modes. For the remaining purposes the PT nesting structure was not identified and the nesting structure that gave the best fit to the data for 10 of the 14 purposes was one with destinations nested beneath modes, implying destination choice to be more sensitive to changes in utility than mode choice. For the final three purposes, a multinomial modes and destinations structure has been adopted.

The models have been validated by comparing the implied VoTs to WebTAG guidance values, calculating elasticities for changes in costs and IVT, and by comparing observed and predicted tour and detour lengths and distributions.

For VoTs, the commute and home–business models validate WebTAG guidance for car driver and bus, with lower values for rail due to the small rail IVT parameters. For the home–shopping, home–escort and home–other travel models, the implied VoTs are lower than WebTAG guidance, which is a consequence of transferring the commute cost function to purposes with lower mean trip lengths. This is an area where future development work could look to improve the models.

The model elasticity validation showed the models to be somewhat inelastic to changes in fuel cost and PT fare. The discretionary travel purposes of home–shopping, home–escort and home–other were key to this result which is related to the transfer of the commute cost function. This further reinforces our recommendation to revisit the model specifications for these journey purposes in future estimation work.

The tour and length validation demonstrated that the models were able to replicate the observed tour length distributions well, and for the majority of modes the observed tour lengths are matched by the model predictions. Car driver tour lengths validated less well for home–shopping, home–escort and home–other, and this again suggests the transfer of the commute cost pivot should be revisited in any future model development work. For the six NHB models, the three PD-based tour models where the estimation sample sizes are small validated less well for tour lengths by mode than the three detour models where the sample sizes are larger.

CNL models were developed with the objective of developing models with more plausible substitution patterns than NL models. The CNL models were estimated using a grid-search method to vary the cross nested logit model parameters with the NL model parameters held fixed. Despite significant effort it was not possible to identify CNL models suitable for policy testing that yielded a significant improvement in fit to the observed LTDS choices for either commute or home–other travel. Holding the NL model parameters fixed in the grid search was key to this result. Our recommendation here is that TfL should investigate the potential of software packages that allow a formal estimation of a CNL model rather than seek to estimate the models using a grid-search approach with the NL model parameters held fixed. Software options here for further investigation include an enhanced version of ALOGIT, NLOGIT, Biogeme, Larch, Ox and R. However, any software package needs to be able to deal with mode-destination choice models with over 1,000 destination alternatives.

In summary, new NL mode-destination models containing detailed segmentation have been developed that are suitable for model implementation.

We have also identified a number of areas where further model estimation work would be valuable:

- Our main recommendation in any future model development work is to revisit the specification of the home–shopping, home–escort and home–other travel models with a view to achieving higher VoTs and higher elasticities to changes in fuel cost and PT fare.
- We recommend investigating the ability of the shopping model to predict travel to large shopping centres, and if necessary introducing new destination constants into the model to capture the attractiveness of such destinations. This would ensure that any impact these terms may have on the behavioural parameters in the model are captured before the model is taken forward to the calibration stage.
- We also recommend adding parking search time to the model specification for all purposes (currently only included for home–other) by adding parking search times to the car time terms. This enhancement would ensure that the model is fully responsive to forecast changes in parking search times.
- Finally, we recommend working with Jacobs to assemble a more complete database of tertiary education enrolments that includes further education enrolments as well as enrolments at university campuses, and then re-estimating the home–tertiary education model using the improved tertiary enrolment data. This would improve the distribution patterns predicted by the tertiary education model, since enrolments better represent patterns of tertiary education demand than employment.

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Appendix A. Tour building note

A.1. Introduction

This note presents a summary of the LTDS tour building analysis. Section 2 presents a brief overview of the tour-based modelling approach. Section 3 details some of the key assumptions, namely how trip-level and stage-level data have been used, the periods of LTDS data included in the tour building, the treatment of modes and purposes, and the allocation of trips and tours to time periods. The note concludes in Section 4 with recommendations to TfL in terms of the tour samples to use for model estimation.

A.2. Overview of the tour-based approach

A full home-based tour is a series of linked trips starting and finishing at the individual's home. The purpose of a home-based tour is determined by identifying the *Primary Destination* (PD) of the tour.

Most tours (81 per cent) comprise a direct trip to the PD and home, such as home–work–home. For these tours, the PD is simply the destination travelled to on the first trip of the tour.

In the tour building, HB tours are identified first. For each HB tour a primary destination (PD) is identified that determines the purpose of the tour.

To determine the PD for home-based tours comprising three or more trips, the following rules have been used:

1. Apply the following purpose hierarchy (i.e. the PD is the destination associated with the trip which is highest in the hierarchy):
    a. Work
    b. Employer's business
    c. Education
    d. All other purposes;
2. If after step 1 there are still ties,[17] take the PD as the tied destination at which the most time was spent;
3. If after step 2 there are still ties, take the PD as the tied destination most distant from the home;
4. If after step 3 there are still ties, define the PD as the first tied destination visited.

[17] For example, in the trip chain home–shopping–shopping–home, both shopping destinations are at level d in the hierarchy and so a PD cannot be identified.

Once the PD has been determined, we can define the outward tour leg as the journey from the home to the PD, and the return tour leg as the journey from the PD back to the home.

It is possible to observe *half tours*, which can occur in two ways:

- Chains of trips where the *origin* purpose for the first trip recorded on the survey day is not the home – these are return half tours, observed at the start of the survey day, e.g. a nightshift worker returning home;
- Chains of trips that depart from the home but do not return to the home on the survey day – these are outward half tours, for example an individual who leaves home on the survey day to visit a friend and stays overnight at their friend's house, or a nightshift worker leaving for work.

Some half tours may be coding errors, where individuals have only recorded partial information about their trip chains. In the LTDS data, the outbound leg is recorded more often than the return leg. Trip chains where the respondent never visits their home during the survey day are dropped.[18]

Our proposed approach to modelling half tours is, for ***frequency modelling****, to include outward half tours but to drop return half tours, the logic being return half tours are more subject to coding errors, and then to assume each outward half tour is a return tour – this approach ensures that we best represent total travel. For* ***mode-destination modelling****, our proposed approach is to include full tours only, i.e. to drop all half tours.*

For some tours more complex chains of trips are observed, such as home–education–work–home. HB tours will be determined as discussed above. Linked trips made during the course of an HB tour that do not depart from or arrive at home will be defined as NHB trips. The travel associated with these trips will be modelled in two ways: firstly, as **PD-based tours**, i.e. a series of linked trips starting and finishing at the same PD, for example if an individual makes a lunchtime trip to the shops (and back to work) during their work day; secondly, as **NHB detours** made during the outward or return legs of HB tours, i.e. a single trip to or from the PD, for example if an individual makes a diversion on their trip back home to pick up a child from school. For NHB detours we model up to one detour per outward HB tour leg, and up to one detour per return HB tour leg.

These two cases are illustrated by the examples in the following figures. In Figure A.1, trips (2) and (3) form the NHB PD-based tour. The associated HB tour is formed by trips (1) and (4).

[18] Just 0.2 per cent of trips in the 2010–2012 LTDS data are from trip chains that never visit the home during the survey day.

Figure A.1. PD-based tour example

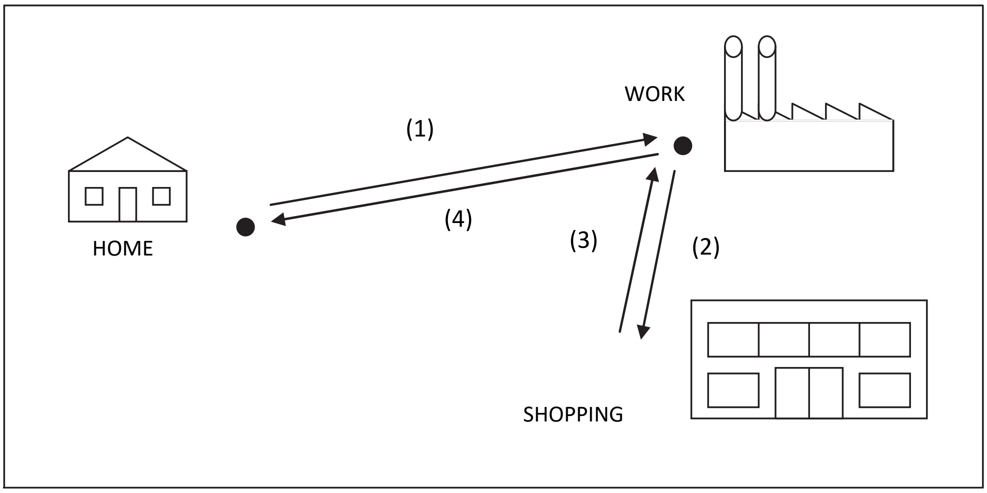
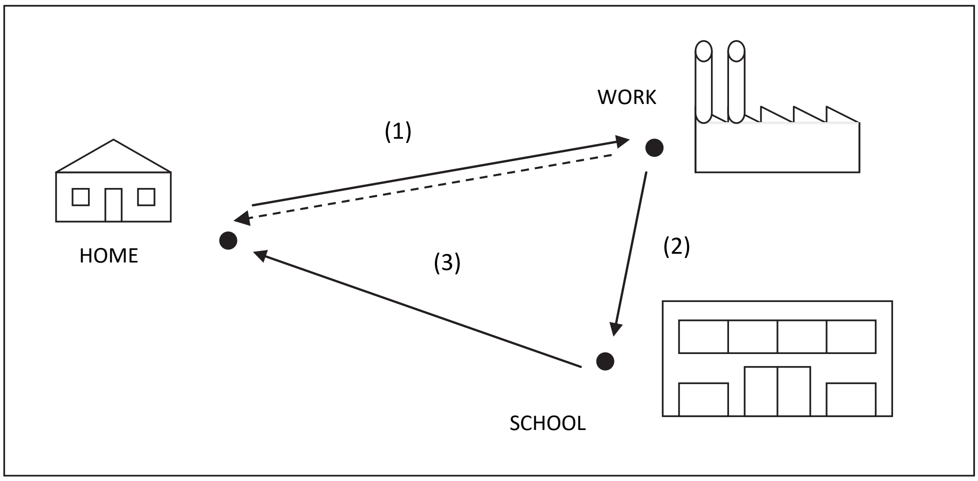


Figure A.2 presents an example that shows how a non-home-based (NHB) detour can occur. Trip (2) forms the NHB detour. The HB tour is assumed to be a direct return tour, and the dotted line represents the return leg that is modelled. The assumption is that the mileage associated with trip (3) that is not modelled is equivalent on average to the mileage associated with the return leg. This assumption was investigated in depth during the development of the first version of the Sydney Strategic Travel Model (STM) in the early 2000s. It was validated in that context by comparing mean detour kilometrage associated with the approach and the total kilometrage associated with the observed trip chain; this demonstrated the approach to be reasonable when examining total trip kilometrage across the study area.

Figure A.2. NHB detour example



A.3. Key assumptions

A.3.1. Use of stage and trip data

The tour building has been undertaken principally using *trip-level* data (a trip is a movement between two locations where activities are undertaken).

Stage-level data cover travel between two locations by a given mode. A trip may constitute more than one stage, for example an individual may travel from home to work (one trip) by walking to a tube station, then taking the Underground, and then walking on to their workplace (three stages: walk, Underground, walk). Stage-level data have only been used to determine the mode of travel for the trip and tour; this issue is discussed further in Section A.3.3.

A.3.2. Time frame of the LTDS data used in the tour building

Following discussions involving TfL, three years of data (2010–2012) were used in the tour building process. The LTDS survey collects data by UK financial year (i.e. April to the following March) but since individual interviews are dated it was straightforward to process 2009/10–2012/13 LTDS data to create a 2010–2012 sample.

When processing the 2012 data there was a need to take account of the impact of the 2012 Olympic and Paralympic Games. While LTDS data were collected throughout the period of the games, it would be expected that the travel patterns of Londoners would be impacted both by the games and their associated impact on transport services. *Therefore, following TfL's advice, LTDS data from 9 July to 23 September 2012 inclusive have been excluded from the tour building analysis.*

Only weekday records were retained in the tour building, as travel patterns would be expected to be significantly different at weekends and are not currently within the scope of the LTS model.

A.3.3. Mode hierarchies

In the LTDS data, each trip record comprises one or more stages, with each stage mode recorded. To determine the main and access mode for each trip, the mode hierarchies detailed in Table A.1 have been applied to the stage-level data. The mode hierarchies are based on those used in the PRISM West Midlands model; very similar hierarchies have been used in other RAND Europe models that work with a tour-based approach.

It is noted that:

- The main and access mode hierarchies differ;
- If there is only one trip on a tour leg then only a main mode is defined;
- If there is more than one trip on a tour leg then the access mode is defined from the trips *other than* the trip associated with the main mode.

Table A.1. Mode hierarchy

ID	Main mode	Access mode
1	train, park and ride	car driver
2	train	motorcycle
3	other rail	car passenger
4	bus/coach	other
5	car driver	taxi
6	motorcycle	train, park and ride
7	car passenger	train
8	other	other rail
9	taxi	bus/coach
10	cycle	cycle
11	walk	walk

Note: 'other rail' includes the Underground and DLR.

The mode with a lower ID in the table above refers to a higher level in the hierarchy. Therefore when deriving the main mode from the stage data, public transport has a higher level of mode hierarchy compared to the car and other modes. The access mode is determined from the modes used in a trip, excluding the main mode.

Table A.2 details the link between the LTDS stage main mode and the mode hierarchy when deriving the main mode of a trip from the constituent stages.

Table A.2. Matching the LTDS stage main mode with the mode hierarchy

Stage mode		Recoded mode	
1	walk (roller blades/scooters)	12	walk
2	pedal cycle	11	cycle
3	car driver	6	car driver
4	car passenger	8	car passenger
5	motorcycle rider	7	motorcycle
6	motorcycle passenger	7	motorcycle
9	van (small) driver	6	car driver
10	van (small) passenger	8	car passenger
11	van/lorry (other) driver	6	car driver
12	van/lorry (other) passenger	8	car passenger
13	bus (public)	4	bus/coach
14	bus (school/work)	4	bus/coach
15	dial a ride	9	other
16	coach	4	bus/coach
17	Underground	3	other rail
18	DLR train	3	other rail
19	National Rail/Overground	1	train
20	Tramlink	4	bus/coach
21	taxi (London black cab)	10	taxi
22	taxi (other/minicab)	10	taxi
23	plane/boat/other	9	other

Motorcycle (recoded mode 7) and other (recoded mode 9) modes are retained in the trip-level analysis. However, it has been agreed with TfL and the LTS study team that these modes will not be retained in the mode-destination models: these modes account for just 0.5 per cent of trips in the 2010–2012 LTDS data (Table A.4).[19] They are therefore excluded from the tour and detour tabulations presented below.

A.3.4. Journey purposes

The LTDS data record 14 different journey purposes, plus two codes for missing and not asked. The 'not asked' response is allocated when it is implicitly clear to the interviewer that the individual is at home at the start of the trip. Table A.3 shows the allocation of LTDS purpose codes and how these are allocated to aggregated purposes and the hierarchy of these for the mode and destination model.

[19] 500 motorcycle + 174 other gives 674 /133641 = 0.5 per cent.

Table A.3. Allocation of LTDS purpose codes to purpose hierarchy codes

LTDS purpose code		Purpose hierarchy	
98	missing	-1	missing
99	not asked	1	home
1	home	1	home
2	usual workplace	2	work
3	delivering/loading	3	employer's business
4	other work	3	employer's business
5	entertainment/sport/social	4	other travel
6	shopping	5	shopping
7	personal business/use services	4	other travel
8	education (as a pupil)	6	education
9	hotel/holiday home	4	other travel
10	drop off/pick up – work	7	escort other
11	drop off/pick up – school/college	8	escort school
12	drop off/pick up – other	7	escort other
13	worship/other religious observance	4	other travel
14	other	4	other travel

It is noted that while 'other travel' has all been allocated to purpose hierarchy 4, some analysis to look at variation in mode shares and tour lengths across the five LTDS purposes that are allocated this hierarchy code has been undertaken. This analysis is presented in Section A.4.

A.3.5. Time periods

Three time periods are represented in the highway and PT assignments:

- AM peak: 07:00–10:00
- Inter-peak: 10:00–16:00
- PM peak: 16:00–19:00.

At present there are no off-peak assignments (i.e. for the 19:00–07:00 period). For the mode-destination modelling work it is proposed to use assignments from the inter-peak, possibly with some adjustments to the highway level-of-service to take account of differences in the level of congestion and public transport services between the inter- and off-peak periods. *This decision does not need to be made to complete the tour building, but an approach for representing the off-peak for highway and PT modes will be required for the mode-destination modelling.*

A.4. Analysis

A.4.1. Validation of mode hierarchy application

Table A.4 presents the comparison of the trip-level main mode derived from the mode hierarchy to the existing 'thmmodec' trip-level mode variable. The 'thmmodec' variable was derived by SYSTRA from the LTDS data to provide a variable with consistent mode categorisations across years.

Trips on the main diagonal are those where the two modes are the same. Encouragingly, the comparison shows a high level of consistency: only 16 out of 133,641 trips (0.01 per cent) have different modes allocated by applying the PRISM-derived mode hierarchy over stages compared to the trip-level variable.

Table A.4. Comparison of trip modes, calendar years 2010–2012 (excluding Olympic period)

Hierarchy-derived mode	Trip level model LTDS mode (thmmodec)										Total
	train	other rail	bus/coach	car driver	motor-cycle	car passenger	other	taxi	cycle	walk	
train	6,942	0	0	0	0	0	0	0	0	0	6,942
other rail	0	8,669	0	0	0	0	0	0	0	0	8,669
bus/coach	0	0	17,771	0	0	0	0	0	0	0	17,771
car driver	0	0	0	36,829	0	0	2	6	0	0	36,837
motorcycle	0	0	0	0	498	2	0	0	0	0	500
car passenger	0	0	0	0	0	18,631	2	3	0	0	18,636
other	0	0	0	0	0	0	173	1	0	0	174
taxi	0	0	0	0	0	0	0	1,441	0	0	1,441
cycle	0	0	0	0	0	0	0	0	2,978	0	2,978
walk	0	0	0	0	0	0	0	0	0	39,693	39,693
Total	6,942	8,669	17,771	36,829	498	18,633	177	1,451	2,978	39,693	133,641

A.4.2. Home-based tour analysis

In this section a number of analyses of 2010–2012 LTDS data are presented. Given that the new LTS will be estimated with a 2011 base year, these analyses consider whether using 2010–2012 data in order to provide larger sample sizes for model estimation results in any bias to mode share and tour length.

This section also examines symmetry between outward and return tour modes to assess the impact of assuming that the outward tour mode defines the mode of the tour as a whole, and cross-tabulates the tour mode with travel purpose to identify for each travel purpose the sample sizes by mode available for model estimation.

A.4.2.1. Variation in purpose shares over the 2010–2012 period

Table A.5 summarises the HB tour samples by purpose and year. As discussed above, tours made by motorcycle and other modes have been dropped from the tabulations as these modes will not be included in the mode-destination models. These data allow us to examine: (1) whether using 2010–2012 data provides sufficient sample sizes for estimation; and (2) whether there are significant changes in the purpose share between years. Table A.5 also details the number of households interviewed per year and the overall average tour rate per household.

Table A.5. Home-based tours by purpose and year

Tour purpose	2010	2011	2012	2010–2012	2010	2011	2012	2010–2012
work	2,992	3,230	2,243	8,465	24.4%	22.9%	22.0%	23.1%
employer's business	984	974	721	2,679	8.0%	6.9%	7.1%	7.3%
other travel	3,411	4,084	2,805	10,300	27.8%	28.9%	27.6%	28.2%
shopping	2,147	2,532	1,650	6,329	17.5%	17.9%	16.2%	17.3%
education	1,592	1,868	1,526	4,986	13.0%	13.2%	15.0%	13.6%
escort other	449	504	460	1,413	3.7%	3.6%	4.5%	3.9%
escort school	703	919	776	2,398	5.7%	6.5%	7.6%	6.6%
Total	12,278	14,111	10,181	36,570	100.0%	100.0%	100.0%	100.0%
Households	5,486	6,098	4,392	15,976				
Tours/household	2.238	2.314	2.318	2.289				

The number of tours for year 2012 is less than 2010 or 2011, which is sensible as we have excluded LTDS data that were collected during the Olympic period. The higher number of tours in 2011 relative to 2010 is explained by a higher number of households being sampled in 2011, rather than being due to a change in tour frequency between 2010 and 2011.

Does using 2012–2012 LTDS data provide sufficient sample sizes?

Yes in terms of overall data, though we need to look at total tours by mode to be definitive. The key concern was the employer's business sample size; however, experience from other models indicates that 2,679 tours should be sufficient for model estimation.

Are there significant changes in purpose share between years?

There are no significant differences in purpose share between years and therefore using the 2010–2012 sample data gives a significant advantage relative to using 2011 data alone. There are some fluctuations in the share of commute, employer's business and education tours, which may relate to changes in the economy.

A.4.2.2. Mode symmetry analysis over the 2010–2012 period

The tour building analysis identifies separate modes for the outward tour leg from the home to the PD, and for the return tour leg from the PD back to home.[20] These modes are not necessarily the same and therefore Table A.6 presents an analysis of mode symmetry. Cases where the outward and return modes are the same are shown on the main diagonal, which is highlighted in blue.

[20] The outward tour leg mode is determined from the trip chain on the outward tour leg; the return tour leg mode is determined from the trip chain on the return tour leg.

Table A.6. Mode symmetry analysis

Outward tour mode	Return tour mode								Total
	train	other rail	bus/coach	car driver	car pass.	taxi	cycle	walk	
train	90.1%	4.2%	2.3%	0.4%	1.4%	1.2%	0.2%	0.2%	100.0%
other rail	2.7%	88.7%	4.9%	0.1%	0.9%	1.8%	0.1%	0.7%	100.0%
bus / coach	1.0%	1.6%	87.7%	0.3%	3.8%	1.5%	0.0%	3.9%	100.0%
car driver	0.1%	0.1%	0.2%	98.8%	0.5%	0.0%	0.0%	0.3%	100.0%
car passenger	0.5%	0.5%	4.3%	1.2%	89.1%	0.5%	0.0%	4.0%	100.0%
taxi	1.7%	8.6%	13.4%	1.3%	6.9%	64.7%	0.0%	3.4%	100.0%
cycle	0.2%	0.5%	0.5%	0.2%	1.2%	0.2%	95.7%	1.5%	100.0%
walk	0.1%	0.3%	3.4%	0.3%	1.9%	0.4%	0.1%	93.6%	100.0%
Total	6.6%	8.0%	16.0%	28.0%	11.5%	1.1%	2.5%	26.3%	100.0%

Levels of symmetry are high, i.e. people tend to use the same mode of travel on their outward and return tour legs. The highest levels of symmetry are observed for car driver and cycle; for both modes this is logical because typically the car/cycle that the individual used on the outward leg will be taken back home again by them on the return leg (except for cyclists using the cycle hire scheme in one direction).

Our recommendation is to use the outward tour leg mode to define the tour mode, consistent with PRISM West Midlands, Sydney and other RAND Europe model systems.

A.4.2.3. Variation in mode shares over the 2010–2012 period

The variation in the HB tour mode share by year is given in Table A.7. The tour mode is defined using the mode identified from the outward tour leg.

Table A.7. Home-based tours by mode and year

Tour mode	2010	2011	2012	2010–2012	2010	2011	2012	2010–2012
train	827	952	702	2,481	6.7%	6.7%	6.9%	6.8%
other rail	1,003	1,131	831	2,965	8.2%	8.0%	8.2%	8.1%
bus/coach	1,907	2,236	1,670	5,813	15.5%	15.8%	16.4%	15.9%
car driver	3,600	3,928	2,709	10,237	29.3%	27.8%	26.6%	28.0%
car passenger	1,415	1,610	1,082	4,107	11.5%	11.4%	10.6%	11.2%
taxi	71	96	65	232	0.6%	0.7%	0.6%	0.6%
cycle	275	403	266	944	2.2%	2.9%	2.6%	2.6%
walk	3,180	3,755	2,856	9,791	25.9%	26.6%	28.1%	26.8%
Total	12,278	14,111	10,181	36,570	100.0%	100.0%	100.0%	100.0%

The average mode shares for 2010–2012 are not substantially different from those observed in 2011, and on this basis we recommend using the 2010–2012 LTDS data. There is some volatility in the cycle mode share, but this will not impact on the *volume* of cycle tours that are predicted *in future years* as these will be inputted according to a separate procedure that SYSTRA is developing to take account of TfL's exogenous forecast of cycle growth. Furthermore, as these are unweighted numbers they do not necessarily indicate a true trend.

A.4.2.4. Variation in tour distances over the 2010–2012 period

The variation in the HB tour length by year is given in Table A.8. The distances used in this table are taken from the inter-peak highway network.

Table A.8. Home-based tours distance by journey purpose and year (km)

Tour purpose	2010		2011		2012	
	mean	median	mean	median	mean	median
work	22.8	16.4	23.0	16.5	23.2	16.7
employer's business	36.8	20.3	34.1	18.0	36.5	18.7
other travel	12.3	5.3	13.1	5.6	11.9	5.1
shopping	6.8	3.6	6.6	3.6	6.7	3.8
education	8.6	4.2	8.2	4.0	7.8	3.6
escort other	12.1	5.6	11.3	4.9	10.8	4.9
escort school	4.4	2.7	3.7	2.3	4.2	2.4
Total	14.9	6.5	14.3	6.2	14.0	6.0

There are no travel purposes where the tour distances vary significantly between year. Employer's business tours are longest with median distances around half the mean, which would be consistent with a mixture of shorter within-London tours and longer tours to locations outside of London. The shortest tours are for school escort; half of these are made by walk.

A.4.2.5. Mode-purpose cross-tabulation

Table A.9 presents a cross-tabulation of the outward tour mode and the tour purpose, for the 2010–2012 data.

Table A.9. Home-based tours by mode and purpose, 2010–2012

Outward tour mode	Tour purpose							Total
	commute	emp. bus.	other travel	shopping	education	escort other	esc. school	
train	1,476 17.4%	361 13.5%	388 3.8%	64 1.0%	175 3.5%	10 0.7%	7 0.3%	2,481 6.8%
other rail	1,596 18.9%	392 14.6%	487 4.7%	156 2.5%	303 6.1%	23 1.6%	8 0.3%	2,965 8.1%
bus/coach	1,159 13.7%	315 11.8%	1,552 15.1%	1,267 20.0%	1,314 26.4%	45 3.2%	161 6.7%	5,813 15.9%
car driver	2,727 32.2%	1,161 43.3%	2,735 26.6%	1,682 26.6%	88 1.8%	1,003 71.0%	841 35.1%	10,237 28.0%
car passenger	286 3.4%	133 5.0%	1,658 16.1%	769 12.2%	1,094 21.9%	116 8.2%	51 2.1%	4,107 11.2%
taxi	27 0.3%	27 1.0%	139 1.3%	13 0.2%	13 0.3%	10 0.7%	3 0.1%	232 0.6%
cycle	363 4.3%	104 3.9%	252 2.4%	97 1.5%	100 2.0%	5 0.4%	23 1.0%	944 2.6%
walk	831 9.8%	186 6.9%	3,089 30.0%	2,281 36.0%	1,899 38.1%	201 14.2%	1,304 54.4%	9,791 26.8%
Total	8,465 100.0%	2,679 100.0%	10,300 100.0%	6,329 100.0%	4,986 100.0%	1,413 100.0%	2,398 100.0%	36,570 100.0%

It can be seen that the taxi mode share is just 0.6 per cent overall. As a result, for most journey purposes there are not sufficient data to estimate taxi as a separate mode. One option would be to merge taxi with car driver; however, given that TfL want to retain a taxi placeholder in the model this option is not ideal as it would make incorporating future forecasts of higher 'taxi' demand difficult.

Therefore it is recommended that the taxi mode be retained in the model for all travel purposes, but that for some HB tour purposes other data is used to calibrate the taxi mode constant. One option to explore with TfL would be to use more years of LTDS data rather than other datasets.

A.4.2.6. Variation in other travel sub-purposes mode shares and tour lengths

The 'other travel' purpose covers a range of different sub-purposes, specifically:

- Entertainment/sport/social (ESS)
- Personal business/use services (PBUS)
- Hotel/holiday home (HHH)
- Worship/other religious observance (WORO)
- Other (Oth).

The analysis presented in this section investigates the extent to which mode shares and tour distance vary across these five sub-purposes (see Table A.10).

Table A.10. PD-based tours by other travel sub-purpose, 2010–2012

Outward tour mode	ESS	PBUS	HHH	WORO	Other	Total
train	308	74	0	5	1	388
	4.1%	3.0%	0.0%	1.4%	4.5%	3.8%
other rail	359	117	0	9	2	487
	4.8%	4.7%	0.0%	2.5%	9.1%	4.7%
bus/coach	937	513	2	98	2	1,552
	12.6%	20.8%	18.2%	27.1%	9.1%	15.1%
car driver	1,954	692	5	75	9	2,735
	26.3%	28.0%	45.5%	20.7%	40.9%	26.6%
car passenger	1,241	342	0	72	3	1,658
	16.7%	13.8%	0.0%	19.9%	13.6%	16.1%
taxi	77	61	0	1	0	139
	1.0%	2.5%	0.0%	0.3%	0.0%	1.3%
cycle	204	46	0	1	1	252
	2.7%	1.9%	0.0%	0.3%	4.5%	2.4%
walk	2,353	627	4	101	4	3,089
	31.7%	25.4%	36.4%	27.9%	18.2%	30.0%
Total	7,433	2,472	11	362	22	10,300
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Over 96 per cent of tours are to entertainment/sport/social (ESS) and personal business/use services (PBUS) sub-purposes. Bus/coach use is somewhat higher for PBUS but overall the variation in mode shares between these two sub-purposes is not large.

Table A.11 shows the variation in mean tour distance by sub-purpose.

Table A.11. Variation in tour distance by sub-purpose (km)

Sub-purpose	Tour distance	
	mean	median
entertainment/sport/social	13.5	5.5
personal business/use services	10.4	5.3
hotel/holiday home	18.6	4.3
worship/other religious observance	7.0	3.8
other	6.8	4.0
Total	12.5	5.4

The tour distances do vary significantly by sub-purpose, with longer tours to hotels and holiday homes as might be expected. The shortest tours are observed to worship/other religious observance locations and for the 22 tours in the 'other' category.

A.4.3. PD-based tour analysis

The tour building process used to identify PD-based tours identifies the tour mode on the basis of the outward tour leg. This means that it is not possible to analyse mode symmetry for PD-based tours without additional work to modify the tour building code.

It is therefore assumed that mode symmetry applies to PD-based tours as well as HB tours.

A.4.3.1. Determination of PD-based purposes

As described in Section 2, in the RAND Europe tour-based approach NHB travel is predicted as a function of HB travel. The approach that has been used in Sydney and the latest version of PRISM is to accumulate the number of HB tours arriving in each PD zone, and then predict NHB travel as a function of that. Therefore a cross-tabulation of PD and SD purposes was run for PD-based tours, which is presented in Table A.12.

On the basis of the sample sizes of PD-based tours it was decided to segment the models at the production-end (i.e. the PD end) into two segments. These are indicated by the colour coding in Table A.12:

- Work-related (WR) – work plus employer's business
- Non-work-related (NWR) – shopping, other travel, education, escort other, escort school.

At the attraction end (i.e. the SD end) the segmentation was made on the basis of both sample sizes and taking account of variation in the appropriate attraction variables. The same two segments were identified.

Table A.12. PD tour purpose cross-tabulation (detailed purposes)

Production purpose (PD)	Attraction purpose (SD)						Total
	employer's business	other	shopping	education	escort other	escort school	
work	232 87.2%	341 64.6%	414 76.5%	0 0.0%	7 38.9%	10 31.3%	1,004 72.1%
employer's business	34 12.8%	37 7.0%	42 7.8%	0 0.0%	2 11.1%	4 12.5%	119 8.5%
shopping	0 0.0%	79 15.0%	47 8.7%	0 0.0%	7 38.9%	13 40.6%	146 10.5%
other travel	0 0.0%	6 1.1%	4 .7%	0 0.0%	0 0.0%	1 3.1%	11 .8%
education	0 0.0%	51 9.7%	28 5.2%	8 100.0%	0 0.0%	0 0.0%	87 6.2%
escort other	0 0.0%	13 2.5%	5 .9%	0 0.0%	2 11.1%	4 12.5%	24 1.7%
escort school	0 0.0%	1 .2%	1 .2%	0 0.0%	0 0.0%	0 0.0%	2 .1%
Total	266 100.0%	528 100.0%	541 100.0%	8 100.0%	18 100.0%	32 100.0%	1,393 100.0%

The sample sizes for the three possible combinations of production and attraction segment are given in Table A.13.

Table A.13. PD tour purpose cross-tabulation (aggregated purposes)

Production purpose (PD)	Attraction purpose (SD)		
	WR	NWR	Total
WR	264 23.8%	846 76.2%	1,110 100.0%
NWR	0 0.0%	271 100%	271 100.0%
Total	264 19.1%	1,117 42.1%	1,381 100.0%

These three purposes have been used for model estimation.

A.4.3.2. Variation in purpose shares over the 2010–2012 period

Table A.15 shows the variation in the tour samples by purpose and year.

Table A.15. PD tour purpose totals by year

PD tour purpose	2010	2011	2012	2010–2012	2010	2011	2012	2010–2012
WR–WR	83	95	86	264	18.7%	17.8%	21.3%	19.1%
WR–NWR	285	324	237	846	64.3%	60.6%	58.8%	61.3%
NWR–NWR	75	116	80	271	16.9%	21.7%	19.8%	19.6%
Total	443	535	403	1,381	100.0%	100.0%	100.0%	100.0%
Households	5,486	6,098	4,392	15,976				
Tours/ household	8.1%	8.8%	9.2%	8.7%				

There is some volatility in the purpose shares by year. Our conclusion is that this is a sample size effect rather than variation in underlying behaviour and so there would be benefit in pooling across the three years of LTDS data to provide larger samples more representative of the true purpose shares.

A.4.3.3. Variation in mode shares over the 2010–2012 period

The variation in mode share by year is shown in Table A.16. These values are summed across the four purposes.

Table A.16. PD-based tours by mode and year

Tour mode	2010	2011	2012	2010–2012	2010	2011	2012	2010–2012
rail	2	7	1	10	0.5%	1.3%	0.2%	0.7%
other rail	16	34	29	79	3.6%	6.3%	7.1%	5.7%
bus/coach	25	31	23	79	5.6%	5.8%	5.6%	5.7%
car driver	73	77	55	205	16.4%	14.3%	13.7%	14.8%
car passenger	15	18	10	43	3.4%	3.3%	2.7%	3.2%
taxi	6	8	4	18	1.4%	1.5%	1.0%	1.3%
cycle	4	6	3	13	0.9%	1.1%	0.7%	0.9%
walk	299	354	278	931	68.2%	66.4%	69.0%	67.8%
other (excluded)	3	0	0	3	0.7%	0%	0%	0.2%
Total	443	535	410	1,381	100.0%	100.0%	100.0%	100.0%

For train, taxi and cycle, where the mode share is low, there is some volatility in the mode shares because of the small sample sizes, but overall there is no evidence from Table A.16 that using 2010–2012 data to represent 2011 travel conditions will cause bias to the mode shares.

A.4.3.4. Variation in tour distances over the 2010–2012 period

Table A.17 presents the mean our lengths by purpose.

Table A.17. PD-based tours by journey purpose and year (km)

Tour purpose	2010	2011	2012	Mean
WR–WR	10.9	8.7	6.5	8.7
WR–NWR	1.4	1.1	1.3	1.3
NWR–NWR	3.2	2.9	3.7	3.2
Total	3.4	2.9	2.8	3.0

There is some volatility in the mean tour lengths by year; given that this is unsystematic, it is again judged to be a sample size effect. Again, by pooling across the three years more reliable estimates of the true 2011 tour distances should be obtained.

A.4.3.5. Mode-purpose cross-tabulation

Table A.18 presents a cross-tabulation of the outward PD-based tour mode and the tour purpose, for the 2010–2012 data.

Table A.18. PD-based tours by mode and purpose, 2010–2012

Outward PD-based tour mode	Secondary destination tour purpose						Total
	employer's business	other travel	shopping	education	escort other	escort school	
rail	8 3.1%	2 .4%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	10 0.7%
other rail	56 21.4%	13 2.5%	8 1.5%	0 0.0%	2 11.1%	0 0.0%	79 5.7%
bus/coach	18 6.9%	28 5.3%	23 4.3%	3 37.5%	2 11.1%	5 15.6%	79 5.7%
car driver	107 40.8%	39 7.4%	35 6.6%	0 0.0%	12 66.7%	12 37.5%	205 14.8%
car passenger	14 5.3%	17 3.2%	11 2.1%	1 12.5%	0 0.0%	0 0.0%	43 3.2%
taxi	10 3.8%	4 .8%	2 .4%	0 0.0%	0 0.0%	2 6.3%	18 1.3%
cycle	3 1.1%	9 1.7%	1 .2%	0 0.0%	0 0.0%	0 0.0%	13 0.9%
walk	49 17.6%	413 78.7%	453 85.0%	4 50.0%	2 11.1%	13 40.6%	931 67.8%
Total	262 100.0%	525 100.0%	533 100.0%	8 100.0%	18 100.0%	32 100.0%	1,378 100.0%

It can be seen that train tours are only observed for employer's business and other travel purposes. Car driver, car passenger, taxi, cycle and walk are also unavailable for some purposes.

A.4.3.6. Proposed treatment of modes and purposes

In summary, we propose that three purposes be modelled for PD-based tours using 2010–2012 LTDS data:

1. *Work-related tours made during work-related HB tours*
2. *Non-work-related tours made during work-related HB tours*
3. *Non-work-related tours made during non-work-related HB tours.*

The sample sizes by mode for the three proposed PD purposes are presented in Table A.19.

Table A.19. PD-based tours by mode and aggregated purpose, 2010–2012

Outward tour mode	Tour purpose			Total
	WR–WR	WR–NWR	NWR–NWR	
train	8 3.1%	0 0.0%	2 0.7%	10 0.7%
other rail	56 21.4%	19 2.2%	4 1.5%	79 5.7%
bus/coach	18 6.9%	17 2.0%	44 16.3%	79 5.7%
car driver	107 40.8%	49 5.8%	49 18.15	205 14.9%
car passenger	14 5.3%	3 0.4%	26 9.6%	43 3.1%
taxi	10 3.8%	6 0.7%	2 0.7%	18 1.3%
cycle	3 1.1%	7 0.8%	3 1.1%	13 0.9%
walk	49 17.6%	745 88.1%	140 51.9%	931 67.6%
Total	262 100.0%	846 100%	270 100%	1,378 100.0%

It is proposed that:

- *For WR–WR all modes are represented*
- *For WR–NWR taxi and cycle are dropped due to the low sample sizes*
- *For NWR–NWR taxi and cycle are again dropped due the low sample sizes.*

A.4.4. Summary of detour analysis

A.4.4.1. Variation in purpose shares over the 2010–2012 period

Tables A.20 and A.21 show the variation in detour samples by detour destination purpose and year for detours made on outward return legs of PD-based tours respectively.

Table A.20. Outward leg detours by purpose and year

Detour destination purpose	2010	2011	2012	2010–2012	2010	2011	2012	2010–2012
employer's business	93	138	87	318	6.8%	7.5%	7.0%	7.1%
other travel	425	574	349	1,348	30.9%	31.1%	28.1%	30.2%
shopping	335	502	349	1,186	24.3%	27.2%	28.1%	26.6%
education	15	19	11	45	1.1%	1.0%	0.9%	1.0%
escort other	254	278	207	739	18.4%	15.1%	16.7%	16.6%
escort school	255	334	240	829	18.5%	18.1%	19.3%	18.6%
Total	1,377	1,845	1,243	4,465	100.0%	100.0%	100.0%	100.0%
Households	5,486	6,098	4,392	15,976				
Tours/household	25.1%	30.3%	28.3%	27.9%				

Table A.21. Return leg detours by purpose and year

Detour destination purpose	2010	2011	2012	2010–2012	2010	2011	2012	2010–2012
employer's business	153	150	121	424	8.1%	6.4%	7.2%	7.2%
other travel	645	827	533	2,005	34.1%	35.2%	31.9%	33.9%
shopping	718	919	704	2,341	38.0%	39.1%	42.2%	39.6%
education	13	21	17	51	0.7%	0.9%	1.0%	0.9%
escort other	201	247	179	627	10.6%	10.5%	10.7%	10.6%
escort school	159	184	116	459	8.4%	7.8%	6.9%	7.8%
Total	1,889	2,348	1,670	5,907	100.0%	100.0%	100.0%	100.0%
Households	5,486	6,098	4,392	15,976				
Tours/household	34.4%	38.5%	38.0%	37.0%				

Higher numbers of detours are made on return legs of HB tours than are made on outward legs. This is consistent with our experience of the PRISM West Midlands and Sydney models.

In terms of variation in purpose share with year, while there is variation between year it is not systematic. It is thus concluded that this is a sample size effect and that pooling across the three years should give more reliable estimates of the true 2011 purpose shares.

Over half of detours are to shopping or other travel destinations (in both tour directions), and escort travel is the next largest purpose, with more escort tours in the outward direction than the return. For escort school this is due to parents escorting their children to school before travelling on to work. Detours to business locations account for 7 per cent of detours in both directions. Education escort accounts for just 1 per cent of detours (these are tours where an older sibling escorts their younger sibling to school before travelling on to their own education destination).

A.4.4.2. Variation in mode shares over the 2010–2012 period

Table A.22 present the numbers and shares of outward leg detours by mode and year.

Table A.22. Outward leg detours by mode and year

Tour mode	2010	2011	2012	2010–2012	2010	2011	2012	2010–2012
train	32	68	43	143	2.3%	3.7%	3.5%	3.2%
other rail	80	96	68	244	5.8%	5.2%	5.5%	5.5%
bus/coach	205	343	212	760	14.9%	18.6%	17.1%	17.0%
car driver	583	668	476	1,727	42.3%	36.2%	38.3%	38.7%
car passenger	170	247	146	563	12.3%	13.4%	11.7%	12.6%
taxi	12	7	12	31	0.9%	0.4%	1.0%	0.7%
cycle	15	25	18	58	1.1%	1.4%	1.4%	1.3%
walk	280	391	268	939	20.3%	21.2%	21.6%	21.0%
Total	1,377	1845	1243	4,465	100.0%	100.0%	100.0%	100.0%

Car driver accounts for the highest share at 38.7 per cent, followed by walk at just under one fifth. Bus/coach and car passengers have the next highest shares, with the other modes (train, other rail, taxi and cycle) collectively accounting for less than one-tenth of the observations. Again, the variation in mode share between years is put down to relatively small sample sizes rather than underlying changes in behaviour.

Table A.23 presents the return leg detours variation.

Table A.23. Return leg detours by mode and year

Tour mode	2010	2011	2012	2010–2012	2010	2011	2012	2010–2012
train	72	95	79	246	3.8%	4.0%	4.7%	4.2%
other rail	145	162	139	446	7.7%	6.9%	8.3%	7.6%
bus/coach	206	253	194	653	10.9%	10.8%	11.6%	11.1%
car driver	547	619	419	1,585	29.0%	26.4%	25.1%	26.8%
car passenger	198	247	168	613	10.5%	10.5%	10.1%	10.4%
taxi	14	28	13	55	0.7%	1.2%	0.8%	0.9%
cycle	19	42	35	96	1.0%	1.8%	2.1%	1.6%
walk	688	902	621	2,211	36.4%	38.4%	37.2%	37.4%
Total	1,889	2,348	1,670	5,907	100.0%	100.0%	100.0%	100.0%

Differently from the outward leg detour, walk accounts for the highest share at 37.4 per cent, followed by car driver at 26.8 per cent. Bus/coach and car passenger have shares of just over 10 per cent, and the other modes have relatively small shares.

A.4.4.3. Variation in detour distances over the 2010–2012 period

Tables A.24 and A.25 present the detour sample sides alongside the mean tour lengths, by purpose and by year.

Table A.24. Outward leg detours by journey purpose and year (km)

Tour purpose	2010		2011		2012		2010–2012	
	sample	mean	sample	mean	sample	mean	sample	mean
employer's business	93	15.8	138	13.2	87	9.6	318	13.0
other travel	425	4.9	574	4.8	349	4.8	1,348	4.8
shopping	335	2.6	502	2.4	349	2.5	1,186	2.5
education	15	11.0	19	6.3	11	17.3	45	10.5
escort other	254	9.8	278	7.0	207	8.4	739	8.3
escort school	255	5.7	334	5.5	240	5.0	829	5.5
Total	1,377	6.2	1,845	5.3	1,243	5.2	4,465	5.5

For employer's business and education the mean distances fluctuate by year; for employer's business in particular a few longer detours can make a significant impact on the mean distances. For purposes with larger samples there is much less variation between years and thus, overall, using the 2010–2012 sample is judged to be reasonable on the basis of detour lengths.

Table A.25. Return leg detours by journey purpose and year (km)

Tour purpose	2010		2011		2012		2010–2012	
	sample	mean	sample	mean	sample	mean	sample	mean
employer's business	153	13.2	150	11.6	121	12.1	424	12.3
other travel	645	6.1	827	7.0	533	5.3	2,005	6.3
shopping	718	3.2	919	3.4	704	3.9	2,341	3.5
education	13	4.6	21	2.9	17	10.8	51	5.9
escort other	201	10.5	247	8.8	177	11.4	625	10.1
escort school	159	5.1	184	5.9	116	5.1	459	5.4
Total	1,889	5.9	2,348	5.9	1,668	5.9	5,905	5.9

While there is some fluctuation in mean detour length by year no systematic trends of change are observed, and the fluctuation tends to be greater for smaller sample size purposes such as education. Overall, using 2010–2012 data is judged to be reasonable for detour lengths.

Comparing outward and return mean detours lengths (i.e. the final two columns), it can be seen that for a *given travel purpose* there is generally not much difference between the outward and return mean detour lengths.

It is concluded on the basis of detour length that it would be reasonable to model outward and return detours using the same set of behavioural model parameters for cost and level-of-service components.

A.4.4.4. Mode-purpose cross-tabulation

We observe a very small sample size of detours for some mode-purpose combinations; cells containing fewer than ten tours are highlighted in grey in Table A.26. We also observe a very small sample size of detours for education, and for some modes (train, other rail, taxi and cycle) for non-education purposes. The cells that contain fewer than ten tours are highlighted in grey in Table A.27.

Table A.26. Outward leg detours by mode and purpose, 2010–2012

Detour mode	Tour purpose						Total
	employer's business	other travel	shopping	education	escort other	escort school	
train	34 10.7%	67 5.0%	31 2.6%	4 8.9%	4 0.5%	3 0.4%	143 3.2%
other rail	46 14.5%	107 7.9%	60 5.1%	6 13.3%	19 2.6%	6 0.7%	244 5.5%
bus/coach	16 5.0%	293 21.7%	338 28.5%	13 28.9%	30 4.1%	70 8.4%	760 17.0%
car driver	183 57.5%	365 27.1%	294 24.8%	7 15.6%	478 64.7%	400 48.3%	1,727 38.7%
car passenger	8 2.5%	204 15.1%	158 13.3%	4 8.9%	111 15.0%	78 9.4%	563 12.6%
taxi	5 1.6%	17 1.3%	4 .3%	0 0.0%	3 .4%	2 .2%	31 .7%
cycle	9 2.8%	22 1.6%	13 1.1%	3 6.7%	2 .3%	9 1.1%	58 1.3%
walk	17 5.3%	273 20.3%	288 24.3%	8 17.8%	92 12.4%	261 31.5%	939 21.0%
Total	318 100.0%	1,348 100.0%	1,186 100.0%	45 100.0%	739 100.0%	829 100.0%	4,465 100.0%

Table A.27. Return leg detours by mode and purpose, 2010–2012

Detour mode	Tour purpose						Total
	employer's business	other travel	shopping	education	escort other	escort school	
train	33 7.8%	115 5.7%	51 2.2%	0 0.0%	29 4.6%	16 3.5%	244 4.1%
other rail	55 13.0%	229 11.4%	101 4.3%	8 15.7%	30 4.8%	23 5.0%	446 7.6%
bus/coach	52 12.3%	249 12.4%	249 10.6%	16 31.4%	31 5.0%	56 12.2%	653 11.1%
car driver	214 50.7%	367 18.3%	406 17.3%	2 3.9%	382 61.1%	214 46.6%	1,585 26.9%
car passenger	25 5.9%	258 12.9%	159 6.8%	8 15.7%	101 16.2%	62 13.5%	613 10.4%
taxi	8 1.9%	37 1.8%	2 0.1%	0 0.0%	6 1.0%	2 0.4%	55 0.9%
cycle	11 2.6%	52 2.6%	22 0.9%	3 5.9%	5 .8%	3 0.7%	96 1.6%
walk	24 5.7%	698 34.8%	1351 57.7%	14 27.5%	41 6.6%	83 18.1%	2,211 37.5%
Total	422 100.0%	2,005 100.0%	2,341 100.0%	51 100.0%	625 100.0%	459 100.0%	5,903 100.0%

A.4.4.5. Proposed treatment of purposes and modes

To ensure a sufficient sample size for certain groups of detours identified above, there is a need to merge purposes. A further consideration for the detour models is that we can estimate the behavioural parameters from across the total sample of outward and return detours, and then estimate separate mode constants in the outward and return directions. This means that the sample sizes that inform the final treatment of purposes and modes are those pooled across outward and return detours.

Our recommendation is that employer's business travel should remain so that the estimated model parameters can reflect the significantly higher values of time relative to non-business travel. The question then is how best to merge the remaining model purposes. One option considered was to represent shopping and then all other purposes, because of the lower detour lengths for shopping travel; however, the shopping sample sizes are insufficient to allow a separate purpose to be distinguished.

Therefore, we propose that three purposes be modelled:

1. *Work-related detours made in the course of work-related tours*
2. *Non-work-related detours made in the course of work-related tours*
3. *Non-work-related detours made in the course of non-work-related tours.*

Given that the behavioural parameters will be estimated from the merged sample of outward and return detours, Table A.28 summarises the total sample sizes in this way.

Table A.28. Detours by mode and aggregated purpose, 2010–2012

Detour mode	Detour purpose			Total
	WR–WR	WR–NWR	NWR–NWR	
train	67 9.1%	174 7.0%	146 2.0%	387 3.7%
other rail	101 13.6%	329 13.2%	259 3.6%	689 6.6%
bus/coach	68 9.2%	244 9.8%	1,101 15.4%	1,413 13.6%
car driver	397 53.6%	1,048 42.0%	1,867 26.2%	3,312 31.9%
car passenger	33 4.5%	115 4.6%	1,028 14.4%	1,176 11.3%
taxi	13 1.8%	36 1.4%	37 0.5%	86 0.8%
cycle	20 2.7%	66 2.6%	68 1.0%	154 1.5%
walk	41 5.5%	485 19.4%	2,624 36.8%	3,150 30.4%
Total	740 100.0%	2,497 100%	7,130 100%	10,367 100.0%

The combined sample of outward and return detours provides sufficient sample sizes for all modes to be estimated for both detour purposes.

A.5. Summary and recommendations

The tour building has been completed successfully and the suggested approach of using 2010–2012 LTDS data, less the Olympic/Paralympic period, is justified on the basis of sample sizes. In particular, the samples of employer's business tours appear to be sufficient for model estimation.

Treatment of half tours

In terms of half tours, we recommend:

- For frequency, to include *outward* half tours but to drop return half tours, the logic being that return half tours are more subject to coding errors, and then to assume each outward half tour is a return tour – this approach ensures that we best represent total travel;
- For mode-destination modelling, to include full tours only (i.e. to drop all half tours).

LTDS records retained in the tour building analysis

Following TfL's advice, LTDS data collected between 9 and 23 September 2012 inclusive were excluded from the analysis, on the basis that travel patterns at that time were significantly impacted by the 2012 Olympic and Paralympic games. Only weekday records were included in the tour building as LTS is a weekday model; travel patterns are understood to be substantially different at the weekend.

Home-based tour analysis

Drawing on our experience from developing the PRISM, Sydney and other model systems, using 2010–2012 LTDS data provides sufficient sample sizes for model estimation. There are no significant variations in purpose share between years that give cause for concern.

Analysis of mode symmetry, specifically the degree of correspondence between the outward and return tour modes, demonstrated overall levels of mode symmetry to be high (90.1 per cent), particularly for car driver and cycle where in both cases the car/cycle is often parked at the primary destination and then used to make the return journey home again. Based on the mode symmetry analysis it is recommended to use the outward tour mode to define the tour mode, consistent with PRISM, Sydney and other RAND Europe model systems.

The variation in mode share between year of LTDS data (2010, 2011, 2012) was analysed. The average mode shares for the 2010–2012 period are not significantly different from those observed in 2011. There is some volatility in the cycle share but this will not impact on the predicted volume of cycle tours *in future years* as these will be inputted according to a separate cycling propensity procedure.

Similar analysis was undertaken to analyse variation in tour distance by purpose and year. There are no purposes where the tour distances vary significantly by year.

A mode-purpose cross-tabulation was undertaken; this analysis illustrates the samples of tours by mode for each travel purpose that is available for model estimation. For all modes except taxi, our judgement is that the sample sizes are sufficient, though in some cases (e.g. train, cycle) we may need to constrain parameter values as a result of the small sample sizes. For taxi, however, sample sizes are a concern for a number of purposes and TfL are keen for this mode to be represented separately as a placeholder for future modes such as autonomous vehicles.

Analysis of variation in mode share and tour distance across the five sub-purposes that make up home–other travel demonstrated that there were not substantial variations in mode share for those purposes that make up the clear majority of the data, but that there is some variation in mean tour length.

PD-based tour analysis

Due to the way that the tour building procedure operates it was not possible to analyse mode symmetry for PD-based tours. Therefore, consistent with HB tours, it has been assumed that the mode symmetry assumption justified using analysis of HB tours also applies to PD-based tours.

Analysis of the purpose shares for PD-based tours demonstrated that more than 96 per cent were made to employer's business, other travel or shopping locations.

Examination across all purposes of variation in mode share showed some volatility in the shares for purposes with small sample sizes but no evidence that using 2010–2012 data to represent 2011 travel conditions will cause bias to the mode shares.

We propose that three travel purposes be distinguished for PD-based travel that are segmented according to the home-based tour purpose which forms the production purpose: work-related to work-related, work-related to non-work-related, and non-work-related to non-work-related.

Detour analysis

The recommendations from the detour analysis are also that that three travel purposes be distinguished, again segmented according to the home-based tour purpose that forms the production purpose: work-related detours made during work-related HB tours, non-work-related detours made during work-related HB tours, and non-work-related detours made during non-work-related HB tours.

Appendix B. Model parameter results

This appendix presents tables detailing the model parameters for the final mode-destination model estimated for each travel purpose. The t-ratios define the significance of the parameters relative to a value of 0 except for the structural parameters, where the significance is defined relative to a value of one. The 'mode' column specifies which mode or modes each parameter is applied to; in this column the seven modes represented in the models are abbreviated as follows:

- CD: Car driver
- CP: Car passenger
- Tr: Rail (Tr is for 'Train', which has been used for most of the rail-specific parameters)
- Bs: Bus
- Tx: Taxi
- Cy: Cycle
- Wk: Walk.

Table B.1. Commute model parameter results

Commute model 119				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			8,365	
final log-likelihood			-54,045	
degrees of freedom			49	
Cost parameters:				
cost1t6	Linear cost, HH inc < £35k p.a.	CD,CP,Tr,Bs,Tx	-0.0008	-8.1
cost78	Linear cost, HH inc £35–75k p.a.	CD,CP,Tr,Bs,Tx	-0.0005	-6.4
cost910	Linear cost, HH inc > £75k p.a.	CD,CP,Tr,Bs,Tx	-0.0002	-2.7
LogCost	logarithm of cost	CD,CP,Tr,Bs,Tx	-0.4767	-10.3
Level-of-service parameters:				
CarTime	Car in-vehicle time	CD,CP,Tx	-0.0339	-33.5
CarPDist	Car passenger distance	CP	-0.0137	-4.0
RailTm	Rail in-vehicle time	Tr	-0.0118	-11.7
BusTm	Bus in-vehicle time	Tr,Bs	-0.0275	-32.2
PTOVT	PT out-of-vehicle time	Tr,Bs	-0.0104	-15.5
CyGDist	Cycle generalised distance	Cy	-0.1789	-17.8
WalkDist	Walk distance	Wk	-0.6433	-32.7

Commute model 119				
Parameter	Variable	mode(s)	value	t-ratio
WKIZ	Walk intrazonal constant	Wk	0.3228	3.3
Segmentation parameters:				
CarDMale	Males	CD	0.2663	2.8
TrnMale	Males	Tr	0.4271	6.2
CyMale	Males	Cy	1.0281	5.4
Trn2635	Aged 26 to 35	Tr	0.4391	6.9
Walkgt50	Aged 50 and over	Wk	0.3440	2.9
TInclt25k	Household income < £25k p.a.	Tr	-0.2557	-3.5
TIncgt100k	Household income > £100k p.a.	Tr	0.2007	2.0
CDFTSfEmp	Full-time self-employed	CD	0.5635	3.2
TrnFTemp	Full-time employees	Tr	0.3908	3.7
BusPTEmp	Part-time employees	Bs	0.1411	1.1
WkFTemp	Full-time employees	Wk	-0.3912	-2.9
PTwrkDist	Part-time worker distance term	all modes	-0.0247	-9.3
TrnBlCr	'Blue collar' occupation types	Tr	-1.1042	-13.3
TrSrMgOc	Senior manager occupation types	Tr	0.5272	5.8
TrTrPrfOc	Traditional professional occupations	Tr	0.7311	6.8
BsClIntOc	Clerical / intermediate occupation types	Bs	0.3861	4.0
CyProf	Modern professional occupation types	Cy	0.8863	5.4
OneFreeCar	One car, free car use	CD	0.6103	4.3
2plFreeCar	Two-plus cars, free car use	CD	1.3131	9.0
OneCarComp	One car, car competition	CD	-0.9585	-6.6
PassOpt	Passenger opportunity	CP	1.7393	6.8
CarPNoLic	HH cars but individual has no licence	CP	0.8690	4.5
BusNoCrLic	HH cars but individual has no licence	Bs	0.8861	11.2
CyNoLic	HH cars but individual has no licence	Cy	-1.1935	-3.1
CyHCP	Additional cycling preference for HCP group	Cy	1.3034	5.1
CyGDistHCP	Cycle general. distance, difference HCP group	Cy	0.0188	1.3
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-5.6855	-15.5
Train	Rail (relative to car driver)	Tr	-1.0177	-5.2
Bus	Bus (relative to car driver)	Bs	-0.1355	-0.8
Taxi	Taxi (relative to car driver)	Tx	-4.2612	-9.7
Cycle	Cycle (relative to car driver)	Cy	-6.1679	-16.3
Walk	Walk (relative to car driver)	Wk	-0.7419	-2.5
Destination effects:				
DempDen	Destination employment density	all modes	-0.3477	-7.6
RDempDen	Destination employment density, rail	Tr	0.5394	10.2
Attraction variable				
TotEmp	Total employment	all modes	1.0000	n/a
Structural parameters				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	0.7545	6.7
TR_PT_D	Rel. sensitivity PT modes and destinations	n/a	1.0000	n/a

Table B.2. Business model parameter results

Business model 101				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			2,208	
final log-likelihood			-15,264.3	
degrees of freedom			41	
Cost parameters:				
GCost1t7	Gamma cost, HH income < £50k p.a.	CD,CP,Tr,Bs,Tx	-0.0044	-7.2
GCostge8	Gamma cost, HH income > £50k p.a.	CD,CP,Tr,Bs,Tx	-0.0040	-6.4
gamma	log-linear mixture parameter		0.01	n/a
Level-of-service parameters:				
CarTime	Car in-vehicle time	CD,CP,Tx	-0.0319	-20.9
CarPDist	Car passenger distance	CP	-0.0084	-1.6
RailTime	Rail in-vehicle time	Tr	-0.0062	-2.9
BusTime	Bus in-vehicle time	Tr,Bs	-0.0236	-14.4
PTOVT	PT out-of-vehicle time	Tr,Bs	-0.0107	-7.6
CyGDist	Cycle generalised distance	Cy	-0.2292	-9.0
WalkDist	Walk distance	Wk	-0.6635	-15.6
Segmentation parameters:				
BsFemale	Females	Bs	0.5782	3.3
Tx4650	Aged 46 to 50	Tx	1.3271	2.5
TRFTemp	Full-time employees	Tr	0.4921	3.7
BSFTSfEmp	Full-time self employed	Bs	-0.9685	-4.2
WkPTemp	Part-time employees	Wk	0.9638	3.2
WkStud	Students	Wk	0.9961	3.1
TrOccup3	Senior managers or administrators	Tr	0.7877	3.6
TrOccup6	Routine manual and service occupations	Tr	-1.0905	-4.4
TrOccup8	Traditional professional occupations	Tr	0.6564	2.9
TxOccup1	Modern professional occupations	Tx	1.8453	3.1
TxOccup3	Senior managers or administrators	Tx	2.7830	3.9
BkOccup1	Modern professional occupations	Bk	0.8388	3.0
2plFreeCD	Two-plus cars, free car use	CD	1.1391	5.6
PassOp	Passenger opportunity	CP	1.8157	5.1
1comTR	One car, car competition	Tr	0.6198	3.6
1comBK	One car, car competition	Cy	1.3732	4.2
CycleH	Additional cycling preference for HCP group	Cy	0.8578	1.9
CyGDistH	Cycle general. distance, difference HCP group	Cy	0.0545	1.6
CDFreeP	Freedom Pass	CD	-1.5983	-3.0
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-7.0299	-10.3
Train	Rail (relative to car driver)	Tr	-1.9008	-7.0
Bus	Bus (relative to car driver)	Bs	-0.8145	-3.0
Taxi	Taxi (relative to car driver)	Tx	-5.1695	-6.3
Cycle	Cycle (relative to car driver)	Cy	-5.6503	-8.1
Walk	Walk (relative to car driver)	Wk	-1.9045	-3.8

Business model 101				
Parameter	Variable	mode(s)	value	t-ratio
Destination effects:				
DempDen	Employment density	all modes	-9.67E-06	-8.5
RDempDen	Employment density, rail	Tr	6.40E-06	4.5
DCCZ	Congestion Charge Zone	all modes	0.0000	n/a
RDCCZ	Congestion Charge Zone, rail	Tr	0.7264	5.1
Attraction variable				
TotEmp	Total employment	all modes	1.0000	n/a
Structural parameters				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Rel. sensitivity PT modes and destinations	n/a	0.8626	1.4

Table B.3. Primary education model parameter results

Primary education model 32				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			2,174	
final log-likelihood			-7,284.0	
degrees of freedom			17	
Level-of-service parameters:				
CarTime	Car in-vehicle time	CP	-0.0726	-6.7
CarPDist	Car passenger distance	CP	-0.1463	-5.1
RailTime	Rail in-vehicle time	Tr	-0.0389	-3.2
BusTime	Bus in-vehicle time	Tr,Bs	-0.0537	-14.5
PTOVT	PT out-of-vehicle time	Tr,Bs	-0.0201	-6.5
CyGDist	Cycle generalised distance	Cy	-0.9580	-8.8
WalkDist	Walk distance	Wk	-1.3111	-42.6
TaxiTime	Taxi in-vehicle time	Tx	-0.0851	-2.1
Segmentation parameters:				
BsNoCar	No car in household	Bs	5.6778	7.5
CycleH	Additional cycling preference for HCP group	Cy	3.0879	4.1
WkNoCar	No car in household	Wk	4.1009	7.1
Mode constants:				
Train	Rail (relative to car passenger)	Tr	-6.3183	-5.9
Bus	Bus (relative to car passenger)	Bs	-2.2562	-4.4
Taxi	Taxi (relative to car passenger)	Tx	-11.9607	-5.5
Cycle	Cycle (relative to car passenger)	Cy	-3.4887	-4.4
Walk	Walk (relative to car passenger)	Wk	3.3914	20.8
Attraction variable				
PEnrols	Primary school enrolments	all modes	1.0000	n/a
Structural parameters				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.5296	8.1

Table B.4. Secondary education model parameter results

Secondary education model 27				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			1,105	
final log-likelihood			-4,249.3	
degrees of freedom			16	
Level-of-service parameters:				
CarTime	Car in-vehicle time	CP	-0.1135	-19.7
RailTime	Rail in-vehicle time	Tr	-0.0496	-7.7
BusTime	Bus in-vehicle time	Tr,Bs	-0.0492	-22.9
PTOVT	PT out-of-vehicle time	Tr,Bs	-0.0101	-7.0
CyGDist	Cycle generalised distance	Cy	-0.6631	-4.6
WalkDist	Walk distance	Wk	-0.9321	-21.9
TaxiTime	Taxi in-vehicle time	Tx	-0.0453	-2.6
Segmentation parameters:				
Trgt75k	Household income > £75k p.a.	Tr	1.0769	2.5
BsHHcar	Households owns at least one car	Bs	-1.3027	-5.7
WKnops	No pass for free or reduced travel	Wk	1.6215	4.9
Mode constants:				
Train	Rail (relative to car passenger)	Tr	-1.9331	-4.8
Bus	Bus (relative to car passenger)	Bs	2.0725	5.7
Taxi	Taxi (relative to car passenger)	Tx	-7.2005	-5.9
Cycle	Cycle (relative to car passenger)	Cy	-2.0138	-2.5
Walk	Walk (relative to car passenger)	Wk	2.9828	11.4
Attraction variable:				
SEnrols	Secondary school enrolments	all modes	1.0000	n/a
Structural parameters:				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.7842	2.5

Table B.5. Tertiary education model parameter results

Tertiary model 29				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			1,136	
final log-likelihood			-6,661.8	
degrees of freedom			25	
Cost parameters:				
cost	logarithm of cost	CD,CP,Tr,Bs,Tx	-0.0002	-0.8
LogCost	logarithm of cost	CD,CP,Tr,Bs,Tx	-0.4127	-3.1
Level-of-service parameters:				
CarTime	Car in-vehicle time	CD,CP,Tx	-0.0471	-10.3
CarPDist	Car passenger distance	CP	-0.0177	-1.4
RailTime	Rail in-vehicle time	Tr	-0.0175	-6.9
BusTime	Bus in-vehicle time	Tr,Bs	-0.0311	-18.3
PTOVT	PT out-of-vehicle time	Tr,Bs	-0.0102	-7.9
CyGDist	Cycle generalised distance	Cy	-0.2267	-6.4
WalkDist	Walk distance	Wk	-0.6755	-21.6
Segmentation parameters:				
CPnoCar	No car households	CP	-1.8169	-4.4
CPnwdis	Unable to work due to illness or disability	CP	2.7918	4.4
Tr1com	One car in household, car competition	Tr	0.6013	2.1
TrcplNCh	Couple no children households	Tr	0.3370	1.9
Traglt18	Aged less than 18	Tr	-1.2995	-6.2
BsCplNCh	Couple no children households	Bs	-0.4015	-2.2
CycleH	Additional cycling preference for HCP group	Cy	0.8108	1.3
CyGDistH	Cycle general. distance, difference HCP group	Cy	0.0635	1.3
CyAge2630	Aged 26 to 30	Cy	1.3908	3.5
WkFeml	Females	Wk	-0.3316	-2.2
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-2.5420	-6.2
Train	Rail (relative to car driver)	Tr	-0.4327	-1.5
Bus	Bus (relative to car driver)	Bs	0.5580	2.1
Taxi	Taxi (relative to car driver)	Tx	-3.5080	-5.7
Cycle	Cycle (relative to car driver)	Cy	-4.9037	-6.1
Walk	Walk (relative to car driver)	Wk	0.1651	0.2
Attraction variable:				
Edu_Emp	Total employment	all modes	1.0000	n/a
Structural parameters:				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	1.0000	n/a

Table B.6. Shopping model parameter results

Shopping model 111				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			5,751	
final log-likelihood			-23,135.1	
degrees of freedom			51	
Cost and level-of-service parameters:				
CarTime	Car in-vehicle time AND cost contributions	CD,CP,Tr,Bs,Tx	-0.0417	-68.5
RailTime	Rail in-vehicle time	Tr	-0.0188	-4.9
BusTime	Bus in-vehicle time	Tr,Bs	-0.0444	-26.6
PTOVT	Public transport out-of-vehicle time	Tr,Bs	-0.0275	-15.8
CyGDist	Cycle generalised distance	Cy	-0.7614	-12.8
WalkDist	Walk distance	Wk	-1.1508	-44.2
IntraDest	Intrazonal constant	CD,CP,Tx,Cy,Wk	-0.4874	-5.2
CPIZ	Car passenger intrazonal constant	CP	-0.3147	-1.7
CyIZ	Cycle intrazonal constant	Cy	0.0000	n/a
WKIZ	Walk intrazonal constant	Wk	0.5023	4.3
Segmentation parameters:				
1freeCD	One car, free car use	CD	1.9621	2.3
CDgt65	Age greater than 65	CD	-2.1618	-2.5
CDCpC	Couple with children households	CD	2.6461	2.9
CDLnPar	Lone parent households	CD	6.3070	2.9
CPFemale	Females	CP	11.2726	7.8
PassOp	Passenger opportunity	CP	19.5573	8.7
CPCpO	Couple only households	CP	4.8159	4.8
CPSinAdl	Single adult households	CP	4.8264	1.8
CPSinPen	Single pensioner households	CP	8.5959	4.1
TRstud	Students	Tr	9.6704	4.3
TR1com	One car, car competition	Tr	6.6499	3.5
TROccup1	Modern professional occupations	Tr	9.2299	4.7
BsFemale	Females	Bs	4.3299	5.9
NoCarBs	No car in household	Bs	3.8837	4.9
BsLt30	Aged 30 or less	Bs	-2.7173	-2.8
BsLt10k	Household income < £10k p.a.	Bs	1.4960	2.0
BsFTslf	Full-time self employed	Bs	-7.2510	-2.8
BsSinPen	Single pensioner households	Bs	-3.3829	-3.6
Bs2free	Two cars in household, free car use	Bs	-10.2728	-5.2
CycleH	Additional cycling preference for HCP group	Cy	11.1309	4.4
BkMale	Males	Cy	5.5073	2.4
NoLicBk	Cars in household, individual has no licence	Cy	-14.7738	-2.3
1comWk	One car, car competition	Wk	4.3335	5.0
WkSinAdl	Single adult households	Wk	3.9218	4.0
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-45.2696	-11.1
Train	Rail (relative to car driver)	Tr	-35.3351	-9.9

Bus	Bus (relative to car driver)	Bs	-18.8163	-9.3
Taxi	Taxi (relative to car driver)	Tx	-44.7672	-9.0
Cycle	Cycle (relative to car driver)	Cy	-42.3939	-9.9
Walk	Walk (relative to car driver)	Wk	-14.4959	-9.8
Destination effects:				
DPopDen	Destination population density	all modes	-1.225E-05	-2.5
RDPopDen	Destination population density, rail	Tr	-2.844E-05	-1.8
BDPopDen	Destination population density, bus	Bs	5.278E-05	6.1
Attraction variable				
L_S_M	Retail employment (base size variable)	all modes	1.0000	n/a
Size_ret	Retail floorspace	all modes	1.0245	2.1
Size_ser	Service employment	all modes	46.4495	12.2
Structural parameters				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.1150	88.6

Table B.7. Escort model parameter results

Escort model 45				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			3,600	
final log-likelihood			-14304.2	
degrees of freedom			35	
Cost and level-of-service parameters:				
CarTime	Car in-vehicle time AND cost contributions	CD,CP,Tr,Bs,Tx	-0.0338	-81.9
RailTime	Rail in-vehicle time and out-of-vehicle time	Tr	-0.0143	-4.4
BusTime	Bus in-vehicle time and out-of-vehicle time	Tr,Bs	-0.0345	-16.5
CyGDist	Cycle generalised distance	Cy	-0.9136	-7.3
WalkDist	Walk distance	Wk	-1.2078	-48.6
Segmentation parameters:				
CDMale	Males	CD	4.6685	3.3
CDag1730	Aged 17 to 30	CD	-6.0169	-3.0
CD1Comp	One car, car competition	CD	-5.7809	-3.4
CDCplC	Couple with children households	CD	-3.1758	-2.6
CPaggt60	Aged 61 and above	CP	5.9240	1.7
CPcplNC	Couple no children households	CP	5.4103	1.8
CPoccu3	Senior managers or administrators	CP	10.1038	2.6
PassOp	Passenger opportunity	CP	24.5638	3.2
BsNoCar	No car in household	Bs	8.2506	3.0
Bs1Comp	One car, car competition	Bs	-10.4501	-2.4
Bs2Free	Two-plus cars, free car use	Bs	-29.0506	-2.4
BsLonPar	Lone parent households	Bs	5.4679	2.7
CycleH	Additional cycling preference for HCP group	Cy	16.8366	2.8
Cy2Comp	Two-plus cars, car competition	Cy	17.5398	2.4
CyOccu6	Routine manual and service occupations	Cy	15.1243	2.4
WkAg2645	Aged 26 to 45	Wk	5.4955	3.3
WkFTslf	Full-time self employed	Wk	5.9706	2.9
WkCPO	Couple only households	Wk	-11.6103	-3.3
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-65.8092	-4.3
Train	Rail (relative to car driver)	Tr	-49.0783	-3.8
Bus	Bus (relative to car driver)	Bs	-29.0253	-3.6
Taxi	Taxi (relative to car driver)	Tx	-52.4939	-3.8
Cycle	Cycle (relative to car driver)	Cy	-53.8094	-4.1
Walk	Walk (relative to car driver)	Wk	-18.3734	-4.0
Origin effects:				
TrOPDen	Population density (persons square km)	Tr	7.2E-04	2.2
WkOPDen	Population density (persons square km)	Wk	3.7E-04	2.7
Attraction variable				
SizeMult	Total population, base size term	all modes	1.0000	n/a
Size_prm	Primary enrolments size term	all modes	26.0116	3.9
Size_sec	Secondary enrolments size term	all modes	8.8751	3.3

Escort model 45				
Parameter	Variable	mode(s)	value	t-ratio
Size_emp	Total employment, size term	all modes	5.0793	3.6
Structural parameters				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.1061	34.6

Table B.8. Other travel model parameter results

Other model 154				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			8,826	
final log-likelihood			-47,978.5	
degrees of freedom			58	
Cost and level-of-service parameters:				
CarTime	Car in-vehicle time AND cost contributions	CD,CP,Tr,Bs,Tx	-0.0313	-92.3
PrkgTm	Parking search time	CD,CP	-0.0054	-2.7
RailTime	Rail in-vehicle time	Tr	-0.0038	-2.2
BusTime	Bus in-vehicle time	Tr,Bs	-0.0301	-26.6
PTOVT	Public transport out-of-vehicle time	Tr,Bs	-0.0197	-16.9
CyGDist	Cycle generalised distance	Cy	-0.4527	-20.3
WalkDist	Walk distance	Wk	-0.8577	-50.1
IntraDest	Intrazonal constant	CD,CP,Tx,Cy,Wk	-0.3544	-4.6
WkIZ	Walk intrazonal constant	Wk	0.7820	8.5
TxIZ	Taxi intrazonal constant	Tx	-1.3345	-3.3
Segmentation parameters:				
IntraGt60	Intrazonal, aged 60 and above	CD,CP,Tx,Cy,Wk	0.1392	2.0
CPFamle	Female	CP	5.8474	7.3
PassOp	Passenger opportunity	CP	11.9687	8.9
CPcpo	Couple without children households	CP	2.8008	4.2
CP3645	Aged 36 to 45	CP	-2.8582	-3.1
CPSinPen	Single pensioner households	CP	4.3995	3.5
CPDistRl	Short-term health problem that impacts mobility	CP	5.9236	6.7
NoLicTR	Cars in household, individual has no licence	Tr	-4.1041	-3.5
TRlt25	Aged 25 or less	Tr	3.0029	3.2
TRCpC	Couple with children households	Tr	-4.0671	-4.1
TRoccp1	Modern professional occupations	Tr	3.7544	3.9
TR1com	One car in household, car competition	Tr	5.1161	5.1
TRDis	Long-term health problem that impacts mobility	Tr	-14.1087	-3.2
TRGt60	Aged 60 and above	Tr	-4.0830	-5.1
TRdistrl	Short-term health problem that impacts mobility	Tr	-6.7526	-4.6
NoCarBs	No car in household	Bs	4.4007	6.2
BsGt75k	Household income > £75k p.a.	Bs	-2.1848	-2.0
BsFTslemp	Full-time self-employed	Bs	-4.8163	-2.8
BsUnemp	Unemployed	Bs	3.5464	4.2
BsLnPar	Lone parent households	Bs	3.3634	3.0
Bs2free	Two-plus cars in household, free car use	Bs	-7.2910	-5.3
NoCarTx	No car in household	Tx	3.7279	2.4
TXGt60	Aged 60 and above	Tx	4.0938	2.7
CycleH	Additional cycling preference for HCP group	Cy	7.9261	5.0
BKMale	Male	Cy	6.0031	4.1
BkUnemp	Unemployed	Cy	7.4311	4.4
BkOccp1	Modern professional occupations	Cy	4.9165	2.9
Bk1com	One car in household, car competition	Cy	8.8123	5.5
1comWk	One car, car competition	Wk	5.0805	7.1
WkDis	Disability than impacts mobility	Wk	-3.3967	-2.4

Other model 154				
Parameter	Variable	mode(s)	value	t-ratio
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-27.2478	-11.1
Train	Rail (relative to car driver)	Tr	-17.8547	-8.6
Bus	Bus (relative to car driver)	Bs	-15.0580	-9.6
Taxi	Taxi (relative to car driver)	Tx	-35.5024	-9.0
Cycle	Cycle (relative to car driver)	Cy	-39.4942	-10.5
Walk	Walk (relative to car driver)	Wk	-9.7043	-9.9
Origin and destination effects:				
CPOpDen	Population density at origin zone	CP	-2.29E-04	-2.8
TROpDen	Population density at origin zone	Tr	5.19E-04	5.5
BSOpDen	Population density at origin zone	Bs	3.20E-04	4.0
TXOpDen	Population density at origin zone	Tx	7.29E-04	4.6
BkOpDen	Population density at origin zone	Bk	3.21E-04	2.6
WkOpDen	Population density at origin zone	Wk	3.58E-04	5.1
DPopDen	Destination population density	all modes	-5.33E-05	-14.1
RDPopDen	Destination population density, rail	Tr	2.35E-05	2.9
BDPopDen	Destination population density, bus	Bs	5.39E-05	7.5
Attraction variables:				
SizeMult	Population (base size variable)	all modes	1.0000	n/a
Size_Ser	Service employment	all modes	46.4495	12.2
Structural parameters:				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.12	79.1

Table B.9. Work-related to work-related tour model parameter results

Work-related to work-related tour model 15				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			236	
final log-likelihood			-1512.2	
degrees of freedom			18	
Cost and level-of-service parameters:				
CarGTm	Generalised car time	CD, CP	-0.0236	-12.3
RlGTm	Generalised rail time	Tr	-0.0175	-5.9
BsGTm	Generalised bus time	Bs	-0.0434	-5.7
TxGTm	Generalised taxi time	Tx	-0.0094	-3.0
CyGDist	Generalised cycle distance	Cy	-1.2700	-2.7
CarPDist	Car passenger distance	CP	-0.0508	-2.2
WalkDist	Walk distance	Wk	-0.9160	-8.4
Segmentation parameters:				
HBCarD	Home-based mode is car-driver	CD	14.5552	1.6
HBTrn	Home-based mode is rail	Tr	5.1934	1.5
HBBus	Home-based mode is bus	Bs	11.1550	1.5
HBBke	Home-based mode is cycle	Cy	15.2357	1.4
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-0.6850	-0.3
Train	Rail (relative to car driver)	Tr	5.4856	1.5
Bus	Bus (relative to car driver)	Bs	3.1803	1.1
Taxi	Taxi (relative to car driver)	Tx	-1.7407	-0.6
Cycle	Cycle (relative to car driver)	Cy	-8.9374	-0.9
Walk	Walk (relative to car driver)	Wk	8.7871	2.2
Attraction variable:				
TotEmp	Total employment	all modes	1.0000	n/a
Structural parameters:				
TR_M_S	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_S_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.2003	6.7

Table B.10. Work-related to non-work-related tour model parameter results

Work-related to non-work-related tour model 19				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			819	
final log-likelihood			-2,394.7	
degrees of freedom			16	
Cost and level-of-service parameters:				
CarGTm	Generalised car time	CD,CP	-0.0429	-9.6
RlGTm	Generalised rail time	Tr	-0.0378	-5.4
BsGTm	Generalised bus time	Bs	-0.0399	-4.8
TxGTm	Generalised taxi time	Tx	-0.0064	-2.9
CyGDist	Cycle generalised distance	Cy	-1.0800	-3.5
WalkDist	Walk distance	Wk	-1.5835	-32.9
Segmentation parameters:				
HBCarD	Home-based mode is car driver	CD	7.7137	2.8
HBBus	Home-based mode is bus	Bs	3.6272	2.2
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-3.9633	-1.6
Train	Rail (relative to car driver)	Tr	6.8956	3.3
Bus	Bus (relative to car driver)	Bs	5.3210	2.5
Taxi	Taxi (relative to car driver)	Tx	-1.2702	-0.6
Cycle	Cycle (relative to car driver)	Cy	2.4971	1.3
Walk	Walk (relative to car driver)	Wk	15.2699	4.8
Attraction variable:				
SizeMult	Population (base size variable)	all modes	1.0000	n/a
Size_Ret	Retail employment	all modes	3.8974	6.8
Structural parameters:				
TR_M_S	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_S_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.3905	4.1

Table B.11. Non-work-related to non-work-related tour model parameter results

Non-work-related to non-work-related tour model 22				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			248	
final log-likelihood			-1059.2	
degrees of freedom			18	
Cost and level-of-service parameters:				
CarGTm	Generalised car time	CD,CP	-0.0268	-9.5
RlGTm	Generalised rail time	Tr	-0.0242	-2.9
BsGTm	Generalised bus time	Tr,Bs	-0.0283	-8.6
TxGTm	Generalised taxi time	Tx	-0.0044	-1.5
CarPDist	Car passenger distance	CP	-0.2090	-4.8
CyGDist	Cycle generalised distance	Cy	-1.0448	-2.0
WalkDist	Walk distance	Wk	-1.1750	-15.0
Segmentation parameters:				
HBCarP	Home-based mode is car passenger	CP	5.2644	2.7
HBBus	Home-based mode is bus	Bs	2.4841	2.1
HBBke	Home-based mode is cycle	Cy	9.7586	2.1
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-3.8758	-2.0
Train	Rail (relative to car driver)	Tr	-4.6739	-1.6
Bus	Bus (relative to car driver)	Bs	-0.6795	-0.5
Taxi	Taxi (relative to car driver)	Tx	-10.8220	-2.9
Cycle	Cycle (relative to car driver)	Cy	-7.2206	-1.7
Walk	Walk (relative to car driver)	Wk	4.6306	7.6
Attraction variable:				
SizeMult	Population (base size variable)	all modes	1.0000	n/a
Size_Ret	Retail employment	all modes	29.8457	2.3
Structural parameters:				
TR_M_S	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_S_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.4194	4.9

Table B.12. Work-related to work-related detour model parameter results

Work-related to work-related detour model 21				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			708	
final log-likelihood			-4,547.6	
degrees of freedom			22	
Cost parameters:				
GCost	Log cost parameter	CD,Tr,Bs,Tx	-0.9297	-12.1
Cost and level-of-service parameters:				
CarTime	Car time	CD,CP	-0.0595	-15.1
RailTime	Rail in-vehicle time	Tr	-0.0248	-3.3
BusTime	Bus in-vehicle time	Tr,Bs	-0.0775	-7.7
PTOVT	Public transport out-of-vehicle time	Tr,Bs	-0.0204	-3.8
CyGDist	Cycle generalised distance	Cy	-0.4897	-5.6
WalkDist	Walk distance	Wk	-0.4319	-8.7
TaxiTime	Taxi in-vehicle time	Tx	-0.0570	-2.9
Segmentation parameters:				
CPtcoccup	Technical and craft occupations	CP	1.6444	2.8
BsPTemp	Part-time employees	Bs	0.9091	2.0
TxSrMgr	Senior manager or administrator occupations	Tx	2.4297	4.0
HBCarD	Home-based mode is car-driver	CD	5.4036	11.3
HBCarP	Home-based mode is car-passenger	CP	2.9526	5.4
HBTrn	Home-based mode is rail	Tr	2.4411	7.3
HBBus	Home-based mode is bus	Bs	1.6552	4.3
HBWlk	Home-based mode is walk	Wk	1.4936	3.2
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-6.1761	-9.4
Train	Rail (relative to car driver)	Tr	0.6762	1.2
Bus	Bus (relative to car driver)	Bs	1.7760	3.5
Taxi	Taxi (relative to car driver)	Tx	0.0519	0.1
Cycle	Cycle (relative to car driver)	Cy	-3.8097	-5.9
Walk	Walk (relative to car driver)	Wk	-3.3761	-5.8
Attraction variable:				
TotEmp	Total employment	all modes	1.0000	n/a
Structural parameters:				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	1.0000	n/a

Table B.13. Work-related to non-work-related detour model parameter results

Work-related to non-work-related detour model 30				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			2,431	
final log-likelihood			-15,507.0	
degrees of freedom			24	
Cost and level-of-service parameters:				
CarGTm	Generalised car time	CD,CP	-0.0766	-51.5
RlGTm	Generalised rail time	Tr	-0.0330	-25.5
BsGTm	Generalised bus time	Tr,Bs	-0.0418	-18.5
TxGTm	Generalised taxi time	Tx	-0.0092	-6.9
CyGDist	Generalised cycle distance	Cy	-0.3791	-9.8
WalkDist	Walk distance	Wk	-0.6049	-28.0
Segmentation parameters:				
2PlfrCrD	Two plus cars in household, free car use	CD	1.5382	1.6
PassOpt	Passenger opportunity	CP	4.5584	2.9
Tr1CrComp	One car in household, car competition	Tr	2.1008	2.4
Wk1CrComp	One car in household, car competition	Wl	1.6532	2.2
HBCarD	Home-based mode is car-driver	CD	17.2946	4.0
HBCarP	Home-based mode is car-passenger	CP	12.2338	3.9
HBTrn	Home-based mode is rail	Tr	8.8569	4.0
HBBus	Home-based mode is bus	Bs	7.4340	4.0
HBWlk	Home-based mode is walk	Wk	4.8711	3.7
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-6.7713	-3.8
Train	Rail (relative to car driver)	Tr	-2.1777	-2.1
Bus	Bus (relative to car driver)	Bs	0.1968	0.2
Taxi	Taxi (relative to car driver)	Tx	-6.5600	-4.4
Cycle	Cycle (relative to car driver)	Cy	-3.8213	-3.8
Walk	Walk (relative to car driver)	Wk	3.5615	3.1
Attraction variables:				
SizeMult	Population, base size variable	all modes	1.0000	n/a
Size_Ret	Retail employment	all modes	6.5173	8.7
Size_Ser	Service employment	all modes	9.2187	6.2
Structural parameters:				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	0.2602	4.3

Table B.14. Non-work-related to non-work-related detour model parameter results

Work-related to non-work-related detour model 22				
Parameter	Variable	mode(s)	value	t-ratio
Model fit information:				
observations			6,665	
final log-likelihood			-28,611.2	
degrees of freedom			25	
Cost and level-of-service parameters:				
CarGTm	Generalised car time	CD,CP	-0.1150	-72.6
RlGTm	Generalised rail time	Tr	-0.0461	-22.7
BsGTm	Generalised bus time	Tr,Bs	-0.0662	-40.6
TxGTm	Generalised taxi time	Tx	-0.0181	-9.5
CarPDist	Car passenger distance	CP	-0.0386	-6.5
CyGDist	Generalised cycle distance	Cy	-0.8032	-11.6
WalkDist	Walk distance	Wk	-1.5957	-67.9
Segmentation parameters:				
CrAge60	Aged 60 and above	CD	0.3128	2.0
RlAge60	Aged 60 and above	Rl	-0.3186	-1.5
WkAge60	Aged 60 and above	Wk	0.9181	10.1
BusUnEmp	Unemployed persons	Bs	0.8110	4.5
HBCarD	Home-based mode car driver	CD	4.7537	22.4
HBCarP	Home-based mode car passenger	CP	4.0405	30.3
HBTrn	Home-based mode rail	Tr	4.1592	20.6
HBBus	Home-based mode bus	Bs	1.9000	16.8
HBWlk	Home-based mode walk	Wk	1.8943	14.9
Destination effects:				
DPopDen	Destination population density (persons/km^2)	all modes	-1.01E-05	-2.8
Mode constants:				
CarP	Car passenger (relative to car driver)	CP	-0.2117	-0.9
Train	Rail (relative to car driver)	Tr	-0.0277	-0.1
Bus	Bus (relative to car driver)	Bs	3.2392	12.6
Taxi	Taxi (relative to car driver)	Tx	-1.3952	-3.4
Cycle	Cycle (relative to car driver)	Cy	-0.3899	-1.3
Walk	Walk (relative to car driver)	Wk	4.2175	19.5
Attraction variables:				
L_S_M	Population, base size variable	all modes	1.0000	n/a
Size_Ret	Retail employment	all modes	17.1623	14.2
Size_Ser	Service employment	all modes	6.2364	4.5
Structural parameters:				
TR_M_A	Relative sensitivity main and active modes	n/a	1.0000	n/a
TR_A_PT	Relative sensitivity active and PT modes	n/a	1.0000	n/a
TR_PT_D	Relative sensitivity PT modes and destinations	n/a	1.0000	n/a

Appendix C. Cost skims for example OD pairs

This Appendix tabulates the cost skims that are used for the estimation of the mode-destination model for few example OD pairs. Tables C.1, C.2 and C.3 show the LOS values for these example OD pairs, for highway, rail and bus only modes respectively.

Table C.1. Highway LOS by TP for example OD pairs

Time-period	Origin	Destination	Time (min.)	Distance (km)	CCZ flag	DT flag	Centroid time (min.)	Centroid distance (km)
AM	1119	1674	62.362	27.183	1.00	0	2.219	0.740
	1119	1675	60.706	26.861	1.00	0	2.123	0.708
	1119	1676	62.197	27.375	1.00	0	1.943	0.648
	1119	1677	66.999	21.497	1.00	0	1.938	0.646
	1119	1678	75.190	30.479	1.00	0	1.755	0.585
IP	1119	1674	49.290	25.452	1.00	0	2.219	0.740
	1119	1675	47.450	25.213	1.00	0	2.123	0.708
	1119	1676	48.921	25.735	1.00	0	1.943	0.648
	1119	1677	51.334	26.209	1.00	0	1.938	0.646
	1119	1678	61.758	28.775	1.00	0	1.755	0.585
PM	1119	1674	58.113	25.586	1.00	0	2.219	0.740
	1119	1675	56.111	25.349	1.00	0	2.123	0.708
	1119	1676	57.699	25.869	1.00	0	1.943	0.648
	1119	1677	60.912	22.714	1.00	0	1.938	0.646
	1119	1678	76.894	27.570	0.00	0	1.755	0.585

Table C.2. Rail LOS by TP for example OD pairs[21]

Time-period	Origin	Destination	BRDPEN: boarding penalty (perceived)	IWAITP: initial wait at first boarding point along route followed (perceived)	XWAITP: interchange wait time (perceived)	NTModeTIMEA: non-transit time (actual) comprises access time, interchange time and egress time	TModeCwdCostP: crowding cost time units (perceived)	Rail IVT (actual)	Underground IVT (actual)	DLR IVT (actual)	Croydon Tram Network IVT (actual)	Bus IVT (actual)	Fare (£)
AM	1119	1674	15.7	10.71	15.09	18.44	17.69	4.88	36.66	0	0	9.55	3.83
	1119	1675	16.57	11.21	21.07	17.95	17.84	13.31	21.24	0	0	9.11	3.57
	1119	1676	16.78	10.94	18.51	17.41	17.01	6.51	30	0	0	9.25	3.83
	1119	1677	14.99	10.84	12.98	16.57	17.45	3.12	36.92	0	0	9.41	3.83
	1119	1678	17.23	11.17	24.35	18.58	22.18	14.59	28.5	0	0	9.43	3.3
IP	1119	1674	14.5	14.65	15.09	19.37	15.68	6.68	34.22	0	0	7.65	4.13
	1119	1675	15.41	22.95	21.07	18.48	11.09	14.77	17.55	0	0	8.6	4.13
	1119	1676	15.4	17.06	18.51	18.06	13.45	6.07	32.24	0	0	7.84	4.13
	1119	1677	13.93	12.38	12.98	17.17	15.51	4.56	35.57	0	0	7.68	4.12
	1119	1678	15.67	25.53	24.35	19.57	14.61	16.54	22.56	0	0	8.7	3.87
PM	1119	1674	14.86	13.34	13.21	19.91	9.09	5.52	37.03	0	0	7.82	4.13
	1119	1675	15.7	12.76	19.94	19.56	6.25	13.19	21.99	0	0	8.3	4.13
	1119	1676	15.64	13.88	15.28	18.82	6.77	5.29	34.06	0	0	7.66	4.13
	1119	1677	14.15	12.89	10.94	18.03	8.08	3.8	37.12	0	0	8.07	4.12
	1119	1678	16.15	13.07	23.1	20.32	8.57	15.53	27.21	0	0	8.56	3.87

[21] Note that the attributes used for modelling purposes only are presented in this table. The out of vehicle time component (plus crowding) is calculated as BRDPEN + IWAITP + XWAITP + 2*NTModeTIMEA + TModeCwdCostP. Fare is converted into pence for use in the models.

Table C.3. Bus only LOS by TP for example OD pairs

Time-period	Origin	Destination	BRDPEN: boarding penalty (perceived)	IWAITP: initial wait at first boarding point along route followed (perceived)	XWAITP: interchange wait time (perceived)	NTModeTIMEA: non-transit time (actual) comprises access time, interchange time and egress time	TModeCwdCostP: crowding cost time units (perceived)	Bus IVT (actual)	Fare (£)
AM	1119	1674	37.3	13.09	21.66	16.27	3.06	99.09	3.47
	1119	1675	33.92	13.46	20.68	16	3.52	100.64	3.61
	1119	1676	34.42	13.23	19.92	17.47	2.72	93.93	3.9
	1119	1677	33.42	13.36	19.01	18.6	2.67	94.87	3.9
	1119	1678	40.86	13.52	29.12	15.93	2.95	120.55	5.2
IP	1119	1674	33.63	13.56	24.04	15.61	8.29	94.3	3.47
	1119	1675	30.29	13.55	22.28	14.88	9.87	95.76	3.61
	1119	1676	32.09	13.91	22.62	15.57	7.57	90.07	3.9
	1119	1677	30.59	13.88	21.11	17.1	7.47	91.13	3.9
	1119	1678	36.95	14.08	30.63	14.66	8.27	113.36	4.77
PM	1119	1674	35.12	14.07	22.9	16.01	1.26	95.64	3.47
	1119	1675	32.32	14.08	22.15	15.94	1.37	96.94	3.47
	1119	1676	33.85	14	21.99	16.17	1.13	91.21	3.47
	1119	1677	32.42	14	20.22	18.2	1.07	91.76	3.47
	1119	1678	40.49	14.38	31.05	14.9	0.96	113.68	5.2