DTO MODEL CALIBRATION

Mode Choice and Time of Travel Choice

Final

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SUMMARY

1. The calibration of the DTO AM Peak model covered all five stages, namely:

   - Trip Generation;
   - Trip Distribution;
   - Mode Choice;
   - Time of Travel Choice; and
   - Assignment.

2. This report specifically concerns the calibration of stages three and four (Mode Choice and Time of Travel Choice). This process was segmented by six journey purposes; Home to Work, Home to Education, Home to Business, Home to Shop, Home to Other and Non-Home based.

3. The calibration process involved obtaining two sets of inputs from the neighbouring stages. From the Assignment stage, skims were collected which informed the model of the perceived costs of travelling on a specific mode at a specific hour between each origin-destination (OD) pair. From the Trip Distribution stage, trip matrices were obtained which informed the model of the base year demand, by mode and arrival hour, between each OD pair.

4. Prior to undertaking any calibration it is good practice to analyse and sense check the input data to ensure that there is nothing untoward (e.g. outliers and null values are dealt with accordingly, correlation between the costs is as expected, i.e. as distances increase, generally travel time also increases). The preliminary analysis undertaken here highlighted one area in particular where refinements could be made to the input data in order to improve the calibration. The walk times associated with travellers getting to a Public Transport connection were initially very high (the average walk time for trip originating outside the M50 was 74 minutes). This analysis prompted PT network changes which lead to a revision of these costs and subsequent lowering of the average walk time to within more reasonable bounds.

5. The calibration itself was carried out separately for Time of Travel Choice and Mode Choice. The Time of Travel Choice calibration was undertaken first because this stage occurs at a lower level within the model structure (as compared to Mode Choice) and so there was greater segmentation of the data within this sub-model. Once the Time of Travel Choice calibration was complete, the outputs from this stage were combined to form inputs into the Mode Choice sub model. Outputs from the Mode Choice calibration included a set of Generalised Cost parameter estimates for use within the DTO model and a series of Composite cost matrices that fed into the Trip Distribution Calibration stage (stage two).

6. A multi-objective market simulation tool was used to calibrate the two stages. The tool, developed in a statistical package called STATA, was designed to seek out the best set of parameter estimates that; a) provided an acceptable level of Goodness of Fit between the observed and modelled data and b) more importantly stacked up with our understanding of the real world and what the data analysis had taught us.

7. In order to ascertain that a set of parameter estimates met these criteria, we performed a series of Goodness of Fit and Realism tests on the output. Where it was found that the calibration results were not acceptable, the process was re-run from a different starting point in an effort to seek out an improved calibration. The output contained within this report is therefore the result of a number of iterations. The results represent the best obtained whilst taking account of data quality issues and limited sample size in certain segments.

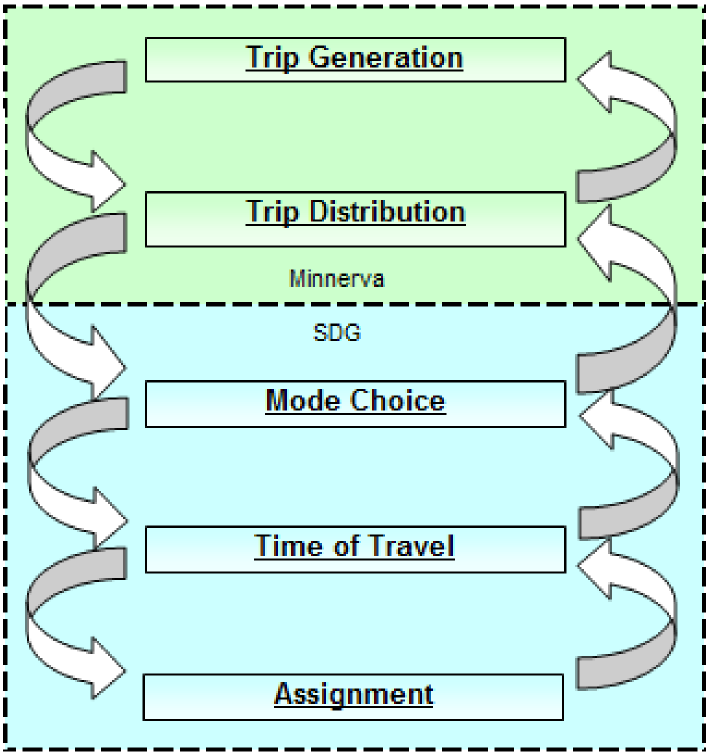
1. INTRODUCTION

1.1 Steer Davies Gleave, in collaboration with consultants Minnerva, were commissioned by the Dublin Transportation Office (DTO) to undertake a calibration exercise of the morning (AM) peak five-stage DTO Transport Demand Model. The five stages of the model are; 1. Trip Generation, 2. Trip Distribution, 3. Mode Choice, 4. Time of Travel Choice and 5 Assignment.

1.2 The model structure is shown in Figure 1.1. The task of calibrating the first two stages was handled by Minnerva. Mode Choice, time of travel and assignment calibration was undertaken by Steer Davies Gleave.

1.3 This report specifically describes the methodology adopted for the calibration of the Mode Choice and time of travel sub models.

FIGURE 1.1 STRUCTURE OF THE AM 5-STAGE DTO TRANSPORT DEMAND MODEL



Mode Choice Model

1.4 Modelling mode choice concerns understanding what factors influence a person's decision to travel by a particular mode (e.g. car, public transport, walk, cycle). Data on these decision factors is taken from the assignment sub modelling process. This data is otherwise known as the cost components, as it can be thought of as the perceived cost elements of travel.

1.5 The costs are a combination of monetary and non-monetary factors; for example in the public transport model these include fare, time spent in the vehicle and the number of transfers. These elements are weighted by a set of parameters in order to derive an overall generalised cost of travelling by a particular mode between an origin-destination pair within the study area.

Time of Travel Choice Model

1.6 The Time of Travel Choice model is concerned with when, between the hours of 7am and 10am, the traveller wishes to arrive at their destination. Thus whereas in the Mode Choice sub-model where the alternatives are car, public transport, walking and cycling, the alternatives available under time of travel are arriving between 7am and 8am, 8am and 9am or 9am and 10am.

Overview to the Calibration Process

1.7 The calibration process for both Mode Choice and Time of Travel Choice models, involves estimating the best set of parameter values such that a number of conditions concerning model fit are met. Once the calibration process is complete, the derived generalised costs are used to estimate what proportion of demand is likely to use a particular mode alternative.

1.8 Before the model is applied (i.e. use of the model to forecast future demand) we must satisfy ourselves that the model is providing realistic results. We do this by subjecting it to a set of realism tests together with validating the output against an independent dataset withheld from the main calibration process.

Contents of the Remainder of this Report

1.9 The remainder of this report is set out as follows:

- In chapter two, we describe the inputs used for the Mode Choice and Time of Travel Choice calibration. We also detail the preliminary analysis that was undertaken ahead of model calibration.
- In Chapter three we detail the methodology used for the calibration of the Mode Choice and Time of Travel Choice sub models.
- In Chapters four and five we present the calibration results of the Mode Choice and Time of Travel Choice sub models respectively.
- Chapter six sets out our conclusions from this exercise and recommendations for future improvements to the overall model.

2. INPUTS AND PRELIMINARY ANALYSIS

Introduction

2.1 In this chapter we describe the specific inputs to the Mode Choice and Time of Travel Choice calibrations. The input data is first subjected to a series of checks to confirm that it is of sufficient quality (after all a model is only as good as the data used within it). Here, we detail the tests we have undertaken on the data to satisfy ourselves that it is fit-for-purpose, and reasonably reflects what one would expect to observe in the real world.

Model Inputs

2.2 There are two categories of inputs used within the discrete choice models; demand and generalised cost components.

Demand Data

2.3 The demand data is provided in the form of trip matrices. These state how many person trips are made between each origin and destination pair. This data is a product of the trip generation and distribution stages (see Figure 1.1). Initially, the matrices are segmented by direction, journey purpose, mode, and time of day. As we are concerned purely with the AM peak, which has proportionately fewer return to home trips than at later points in the day (e.g. PM peak), we aggregate the outward and return journeys to create a set of matrices split by journey purpose, mode and time of day.

Generalised Cost Components

2.4 The data on the generalised cost components is produced in the form of matrices and originate from the SATURN and TRIPS assignment models at the bottom of the process (see Figure 2.1), and flow upwards. The components are mode dependent.

2.5 For highway, the generalised cost components include:

- Distance (km)
- Travel time (minutes)
- Toll (cents).

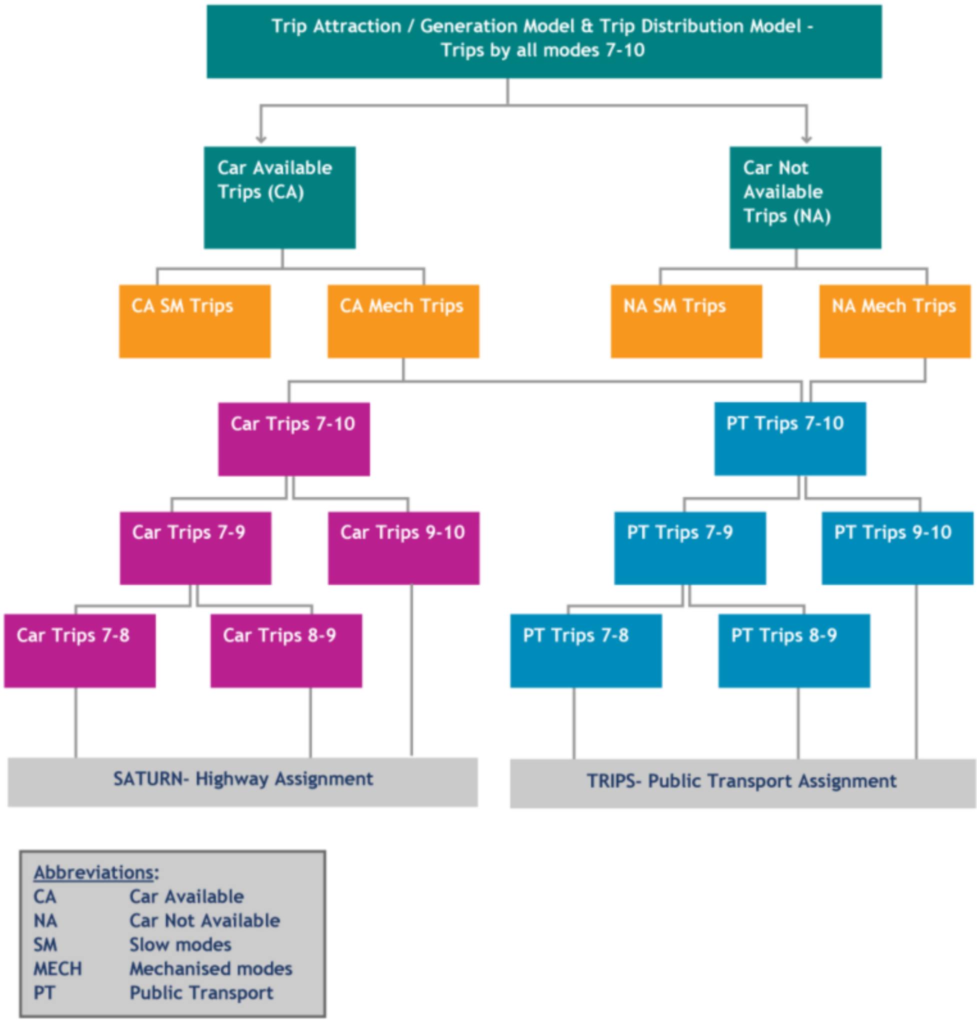
2.6 For Public Transport (PT), the components are:

- In-vehicle time (IVT) (minutes)
- Waiting time (minutes)
- Walking time (minutes)
- Number of transfers
- Fare (cents)
- Crowding IVT (minutes).

2.7 For slow modes (SM), there is one cost component; travel time. This is derived by taking the average highway distance travelled for each OD pair and dividing it by a weighted compound speed that takes account of the ratio of walk and cycle trips along that route.

2.8 The inputs described are used in both the Mode Choice and Time of Travel Choice models. The only difference is the level of segmentation. In Figure 2.1, we note that the first two sub-model stages; Trip Generation and Distribution, are positioned at the top of the structure. The trip matrices generated from these processes are output and fed into the Mode Choice calibration sub-model which attempts to split the total demand into the three modes considered; car, public transport and slow modes (cycling and walking). Note that this process is carried out separately for those trips where a car was available and for those trips where a car was not available. In the case of the latter, no car option exists within the sub model.

FIGURE 2.1 STRUCTURE OF THE CURRENT MODE CHOICE, TIME OF TRAVEL CHOICE AM PEAK MODEL



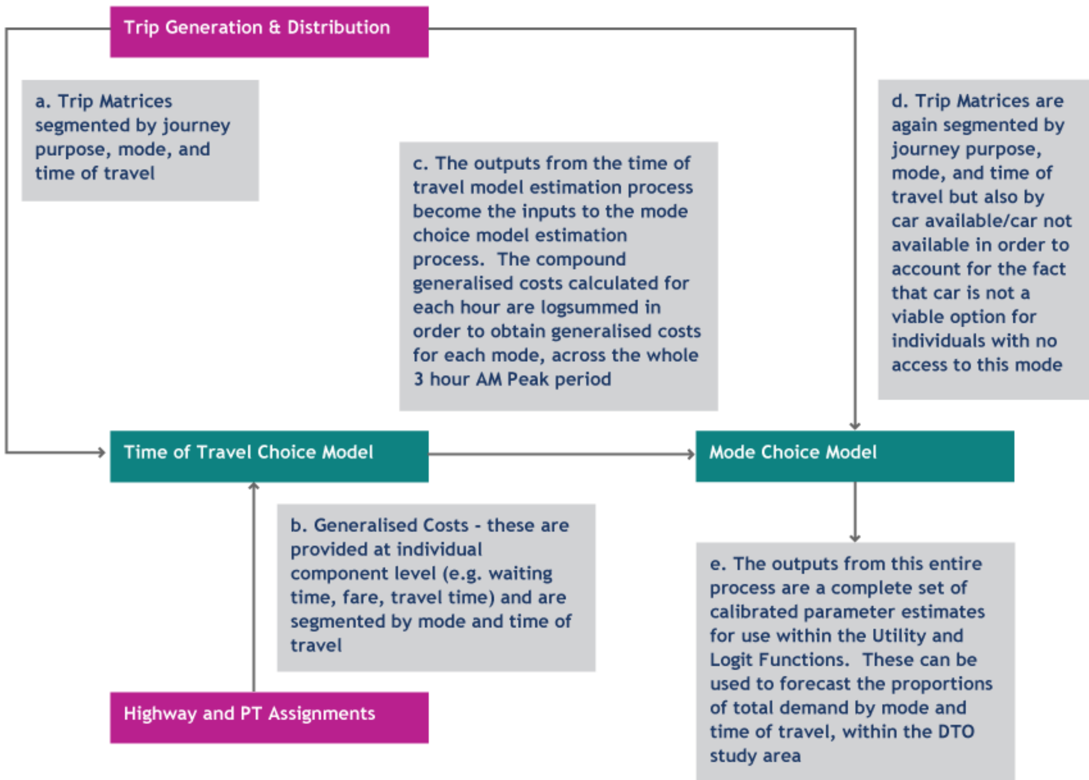
2.9 Once the demand has been segmented by mode, we then consider splitting the demand further into one of the three arrival time bands; 7am to 8am, 8am to 9am and 9am to 10am. In Figure 2.1, this Time of Choice sub-model process is shown as a two tier "nested" structure where trips are first split into time bands 7am to 9am and 9am to 10am before further sub-dividing the first time band into 7am to 8am and 8am to 9am. This is not the only structure that could be considered for the time of choice modelling. For instance, it may be more appropriate to use a flat one-tier structure where all three time periods are on the same level. We began our Time of Choice modelling using the structure shown above. However, we have considered the use of alternative structures where the calibration results suggested a reason to do so (see section 4 for more details).

2.10 The output from the Time of Travel sub models are the (modelled) trips segmented by mode and time of travel and these flow into the highway and PT assignment models. However, in order to split the total trips by mode and time of travel, the two choice sub-models (i.e. Mode Choice and Time of Travel Choice) first require generalised costs which are obtained from the very same highway and PT assignment models. Therefore, we have a situation whereby the input data sources for the Mode Choice and time choice sub-models (Trip Generation and Distribution for the trip matrices and Assignment models for Generalised Costs) are also the recipients of the outputs for these two discrete choice sub models. In the next section, we explain, how in practical terms, we address the simultaneous handling of the trip matrices and generalised costs.

Overview to the Model Calibration Process

2.11 The calibration process is illustrated in Figure 2.2.

FIGURE 2.2 CALIBRATION PROCESS: TIME OF TRAVEL AND MODE CHOICE



2.12 The cost components are first loaded into the Time of Travel Choice model estimation process, segmented by hour-band (7am-8am, 8am-9am and 9am-10am) and mode (PT, highway, slow modes). The demand matrices, segmented by hour-band, mode and journey purpose are then loaded into the Time of Travel Choice process, and the calibration carried out.

2.13 Once the Time of Travel Choice model has been calibrated, the costs are aggregated up to provide one generalised cost per OD pair, per mode, across the whole 7-10am period (the aggregation process involves a logsum of the generalised costs of each individual hour-band). This is repeated for each of the six categories of Journey Purpose as listed in Table 2.1. Note that return journeys were grouped together with their corresponding outward leg journey purpose (i.e. Work to Home grouped with Home to Work) and Non Home Based Business trips with grouped under the Home to Business category as the two types of trips were considered to have a similar Value of Time.

TABLE 2.1 CATEGORIES OF JOURNEY PURPOSE

Category	Directional Journey Purpose Trips
Commute (Home to Work HW)	Home to Work, Work to Home
Home to Education (HE)	Home to Education, Education to Home
Home to Business (HB)	Home to Business, Business to Home, Non Home Based Business
Home to Shop (HS)	Home to Shop, Shop to Home
Home to Other (HO)	Home to Other, Other to Home
Non Home Based (NHB)	Non Home Based Other

2.14 These compound generalised costs then become the cost inputs for the Mode Choice model estimation process. Again, demand matrices are loaded into the Mode Choice model but this time they are segmented by mode, journey purpose and also split by car available (CA)/car not available (NA). The calibration of the Mode Choice model then commences.

Preliminary Analysis & Modification

2.15 Prior to undertaking model calibration, the input data is thoroughly checked. The aim of this stage is to mitigate against the risk of using data within out models which is either erroneous or does not make intuitive sense. Including such data in our models would create additional noise or variability and the resultant set of parameter values estimated would not be as good at explaining the observed demand. The following steps are undertaken during the preliminary analysis and modification stage:

Step1 – Zero Demand

2.16 All OD pairs where there is no observed demand across any of the alternatives (e.g. PT, car, slow modes, 7-8, 8-9 and 9-10) are identified. These cases do not add any value to the explaining capabilities of the model and are thus omitted.

Step 2 – Missing Costs

2.17 All OD pairs with demand should have costs. We analyse the data to ensure this is the case. If we find examples where this does not hold true, further investigation is undertaken by the network modellers. If no costs are obtainable then the remedial action could involve estimating the costs based on those used for neighbouring zones.

Step 3 - Outliers

2.18 Generalised costs for outliers or unusually high average values are checked. We plot the individual generalised cost components and study their distributions to check for the existence of outliers (values numerically distant from the rest of the data). Determining the existence of outliers is a rather subjective exercise but examining the distribution of the data and taking account of the inter-quartile range (the range of values between the 25th percentile and the 75th percentile) can provide a useful means by which to identify extreme values. If such cases are found the costs are re-examined in the first instance.

2.19 An example is provided in Table 2.2, the first table, providing initial results, summarises the average walk time for PT trips arriving between 8am and 9am. The walk times were found to be particularly high for trips starting/finishing outside the M50. This prompted a re-examination of the factors affecting walkers in the PT assignment model. A series of network changes were made, including providing additional walk links in the PT network model, the result of which led to a reduction in walk time (see Table 2.2 and Table 2.3) to within more reasonable limits.

TABLE 2.2 PT TRIPS ARRIVING 8AM-9AM: MEAN WALK TIME - INITIAL RESULTS

O/D	Inside City Centre	Inside M50	Outside M50	Average
Inside City Centre	19.60	26.69	55.88	32.25
Inside M50	27.48	31.98	59.57	33.70
Outside M50	66.30	62.42	108.54	73.77
Overall Average	42.98	41.58	81.12	49.31

TABLE 2.3 PT TRIPS ARRIVING 8AM-9AM: MEAN WALK TIME - REVISED RESULTS

O/D	Inside City Centre	Inside M50	Outside M50	Average
Inside City Centre	19.58	27.14	39.11	28.08
Inside M50	26.72	30.52	42.45	29.51
Outside M50	37.30	41.69	54.52	41.75
Overall Average	31.25	34.02	48.82	34.78

Step 4 - Trends

2.20 Trends in the data are examined and reconciled with what we believe happens in reality. For example, in Table 2.4, the relative magnitudes of the average distance appear reasonable. In other words within the city centre, trips are on average 2.5km, whereas trips outside the M50 are on average 31.1km. The average toll is also higher on those trips in and around the M50. This makes intuitive sense as a higher proportion of these trips are likely to use the toll section of the M50 and thus incur a charge.

TABLE 2.4 HIGHWAY COMMUTING TRIPS ARRIVING 7-8AM: AVERAGE VALUES

Origin	Destination	Average Distance (km)	Average Time (mins)	Average Toll (cents)
From Outside M50	To Outside M50	31.1	35.3	20.92
	To Within M50	28.6	45.2	25.52
	To Inside City Centre	28.2	60.2	4.19
From within M50	To Outside M50	19.3	30.0	27.18
	To Within M50	7.5	22.0	15.22
	To Inside City Centre	7.2	33.1	3.67
From within City Centre	To Outside M50	23.9	37.6	1.04
	To Within M50	6.7	24.4	1.78
	To Inside City Centre	2.5	16.7	0.13

2.21 Once we have satisfied ourselves with the consistency of the data, we proceed onto the calibration. The approach is described in full in chapter 3.

3. METHODOLOGY

Introduction to Discrete Choice Modelling

> *"The Probability of an individual choosing a given option is a function of his/her socio-economic characteristics and the relative attractiveness of the option."*
>
> (Williams 1981)

3.1 By Discrete choice we mean, the selection of an alternative from a finite set of alternatives. In a transport context, this may mean a traveller choosing a mode of transport from either: car, bus, rail or walking; or deciding in which hour to arrive at their destination during the AM peak.

3.2 To understand how we model the traveller's selection process, we must first introduce the concept of "utility" which stems from economics. Utility is a measure of the relative "enjoyment" experienced during the consumption of goods or services. So for example, if a person travelling to work enjoyed using a bus more than rail, we could say their utility for the bus was higher than for rail; they preferred using the bus.

3.3 In discrete choice modelling we typically assume that travellers are 'utility-maximisers'; in other words that they choose an alternative which they perceive to be the most attractive, provided that alternative is available to them.

3.4 By formulating a measure of the attractiveness of an alternative we can contrast it with the alternative options and in doing so estimate the proportion of demand that will use each alternative. An example of a function of "attractiveness" for highway is shown in Figure 3.1. In this function the term "generalised cost" is used which can be considered to be the inverse of utility (or disutility).

FIGURE 3.1 GENERALISED COST FUNCTIONS – CAR AND PT

Generalised Cost of Car = $W_1 \cdot$ ***distance travelled*** $+ W_2 \cdot$ ***time spent travelling***

+ Toll Costs/$(VoT * W_3)$

+ alternative specific constant(ASC)

Generalised Cost of PT = $W_1 \cdot$ ***In-vehicle Time*** $+ W_2$ ***waiting time***

$+ W_3 \cdot$ ***walking time*** $+ W_4 \cdot$ ***no. of transfers***
+fare/$(VoT * W_5) + W_6 \cdot$ ***Crowding***

+ alternative specific constant(ASC)

VoT: Value of Time sourced from the 2004 GEC report *(Parameter Values for Use in Cost-Benefit Analysis of Transport Projects, Goodbody Economic Consultants in association with Atkins - Sep 2004)*. For non-business trips, the VOT value used was 8.1 Euro/person/hour. For business trips, the VOT value used was 26.5 Euro/person/hour.

3.5 In order to model the demand that will use each alternative, we use what is referred to as a logit function which incorporates the derived Generalised Costs. In Figure 3.2 we provide an example of a logit formula used to estimate the proportion of Highway Commuting trips that will arrive between 7am and 8am. The complete set of alternative arrival times the traveller can choose from are 7-8, 8-9 and 9-10.

FIGURE 3.2 LOGIT FORMULA

$$P_{7\text{-}8} = \exp(-scaler*GC_{7\text{-}8}) / (\exp(-scaler*GC_{7\text{-}8}) + \exp(-scaler*GC_{8\text{-}9}) + \exp(-scaler*GC_{9\text{-}10}))$$

Where: "scaler" represents a scaling parameter which is estimated, and GC stands for Generalised Cost.

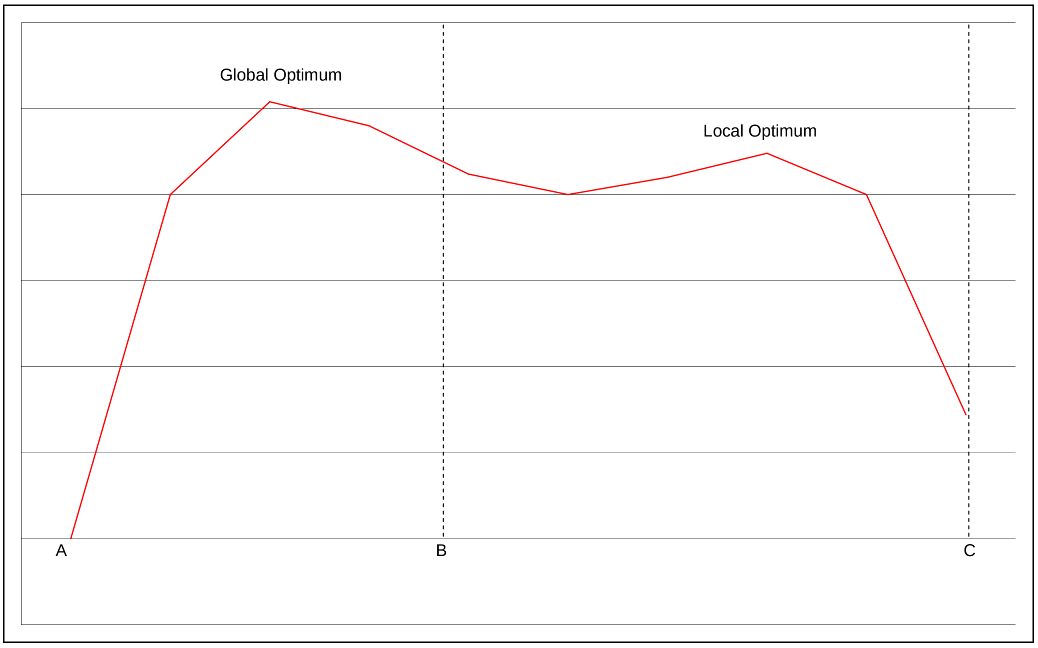
3.6 The result of the logit function is a value between 0 and 1 and is interpreted as the proportion of total demand across all alternatives that select this particular option (in the example above, it would mean the proportion of all highway AM Peak demand that chooses to arrive between 7am and 8am)

3.7 Calibration of a discrete choice model involves estimation of the weights and alternative specific constants in the Generalised Cost functions (*W_1, W_2, W_3, ASC, etc* in Figure 3.1) as well as the scaler parameters in Figure 3.2.

Maximum Likelihood Experiment

3.8 When estimating discrete choice models it is common practice to determine the values of the model parameters by maximising the log-likelihood function. This approach picks the values of the model parameters in such a way as to make the modelled data 'more likely' (to that which is observed) than would be the case with any other set of parameter values. This is a powerful approach, and the set of parameter values it renders as the solution of the estimation problem is often the global optimum (i.e. the highest value within a given domain. Other approaches exist which do not always find the highest value overall but rather the highest value within just a part of the domain – commonly termed a local optimum). An illustration of the two types of optimum is shown in Figure 3.3.

FIGURE 3.3 ILLUSTRATION OF LOCAL AND GLOBAL OPTIMA



3.9 In the above diagram, the domain is AC and the global optimum is the maximum turning point in the sub-domain AB. Some estimation approaches may begin in the sub-region BC and may only find the local optimum without going on to find the global optimum which would represent the best solution.

3.10 Solving the estimation problem using a maximum likelihood approach is also very robust in the sense that it lets us test the significance of each model parameter separately, using statistics such as the t-test. These allow us to examine not only the goodness-of-fit of the entire model but also the adequacy of each individual parameter.

3.11 At an early stage of this study we attempted to estimate the model using Biogeme[1], a programme that specialises in these types of problems. We did this by constructing a data file structured similar to the files created from Stated Preference (SP) survey outputs or travel diaries, but with some adjustments that the nature of the data required. Unfortunately, this model estimation exercise was not successful. The reason for this is not related to the structure of the data file but to the amount and the nature of the information stored in it.

3.12 Failure to estimate logit models using maximum likelihood, when the demand inputs include modal trip purposes only, is very common. It is a direct result of one of the main drawbacks of maximum likelihood algorithms: that is when there is high level of correlation between multiple variables in the generalised cost functions; the procedure may not identify any solution, not even a local optimum. In other words, when demand inputs are not based on rigorously designed survey data (such as in Stated Preference), high correlation between the variables is almost always present. It is therefore extremely difficult to isolate the effect of each of the individual components of the cost functions presented earlier.

3.13 For the purposes of travel demand forecasting we are often willing to compromise on a set of parameter values that forms a local optimum of the model estimation problem, so long as this solution passes some pre-defined validation tests. We are not aware of software tools that can do this through maximum likelihood model optimisation so therefore continued with the model estimation process using an alternative approach.

Market Simulation Experiment

3.14 The model presented in this report was estimated using a multi-objective market simulation tool with an automated solution search algorithm.

3.15 By stating that this is a ***multi-objective*** tool we mean that the choice of the best set of parameters for the Mode Choice model is done by combining several objective functions, rather than one function like in a likelihood maximising process. We use one expression, which we call ***the meta-error***, to combine all objectives, and try to minimise the value of this meta-error. We present all objectives below.

3.16 By stating that this is a ***market simulation tool*** we mean that for each candidate set of parameter values, we generate a full set of mode/time of travel, share

[1] http://transp-or.epfl.ch/page63023.html

estimates for each origin-destination pair, based on the dataset with the components of the generalised cost. We then use the different objective functions mentioned above to test to what extent these estimates meet our needs. We do this repeatedly with different possible parameter sets.

3.17 By stating that we use an ***automated solution search algorithm*** we mean that instead of adopting a trial-and-error approach for examining possible solutions, we use a more systematic technique. It helps us make an intelligent guess of what parameter set has a good chance of performing well, based on what we know on the performance of parameter sets we have already examined. This technique is based on the Downhill Simplex Method which we describe in the next section of this chapter. The algorithm was programmed in a statistical analysis package called STATA[2] and the process is fully automated via the use of "For Loops" that continuously iterate in search for parameter values that further improve (minimise) the value of the meta-error.

3.18 As explained earlier, the process we describe here is dominated by difficulties related to the high correlation between the different components of the generalised cost functions. This high correlation means that when we try to determine the value of each parameter, there seem to be too many degrees of freedom, i.e. too many combinations of parameter values seem equally likely to be the sought solution.

3.19 The standard procedure when estimating models is to go through a calibration process first, and then use some validation tests (or 'realism tests') to verify that the solution chosen in the calibration process is satisfactory. But if a procedure where calibration precedes validation is used to solve a problem with too many degrees of freedom, the validation test is rarely satisfied, and there is a need to loop over the process of calibration and validations repeatedly. This is quite an inefficient process.

3.20 We therefore embark here on a model estimation procedure in which calibration and realism testing are undertaken simultaneously. We define several different objectives; some of them are measures of goodness-of-fit like those used in calibration processes, and some others are typical validation tests. We examine the performance of each candidate set of model parameters based on all these objectives; namely, validation is done at each stage of the calibration process rather than after calibration is complete.

3.21 As explained above, what we practically try to minimise is a meta-error, that is, a weighted average of the values of all objectives. To calculate the meta-error we assign a weight to each objective before the process is run. This weight is determined so that the meta-error is not dominated by any of the objectives; namely, so that once some of the objectives reach plausible values, the meta-error is always more affected by the objectives that have not reached plausible values yet.

3.22 Setting the values of the weights required some preliminary experiments and was based on our judgement of the sensitivities of the different objectives, because an improvement of 0.1 in one objective is not equally important as an improvement of a similar size in another objective. We refrain from presenting the weights used

2 http://www.stata.com/

because they do not have a straightforward meaning, and were subject to continuous refinement throughout the model estimation process. We did this, for example, if we found a solution for the model estimation problem that satisfied all objectives but one; we then increased the weight of the remaining objective, resumed the process with the revised weights, and so on.

3.23 The different objective functions that we have used in the combined calibration/validation process are described in paragraphs that follow.

Objective 1: Minimise error in total trips of each alternative.

3.24 The difference between the observed (i.e. from the input data) and estimated (i.e. from the model output) total number of trips is calculated for each alternative as a proportion of the observed number of trips. The target value for this objective is zero.

Objective 2: Minimise error in the geographical dispersion of demand of each alternative.

3.25 Similar totals of observed and modelled demand do not mean that the model correctly replicates the distribution of this demand across different origin-destination pairs. To examine this spatial distribution we use the RMSWE measure, which stands for Root Mean Squared Weighted Error. It is calculated as follows:

$$\sqrt{\frac{1}{\sum y_i} \cdot \sum \left(\frac{x_i - y_i}{y_i} \right)^2 \cdot y_i} \qquad \text{(Equation 1)}$$

3.26 In equation 1, $\mathbf{x_i}$ represents the modelled flow for a specific alternative for a specific origin-destination pair **i**, and $\mathbf{y_i}$ represents the observed flow for the same alternative and origin-destination pair. The term within the bracket is simply the error for a single **i**, that is the normalised difference between the observed and modelled flows. It is squared so that errors of different signs do not cancel each other out, and also in order to give larger errors a bigger weight. The multiplication by $\mathbf{y_i}$ gives larger flows a greater influence. The ideal value of the RMSWE is zero.

Objective 3: Ensure that fuel cost elasticity in the model is within the range recommended in WegTAG.

3.27 This is, in fact, a constraint rather than an objective function, but it is converted into an objective function by defining an expression (that we wish to minimise) that includes a high penalty if the fuel cost elasticity implied by the model is outside the range specified in WebTAG. The market simulation tool calculates, for each origin-destination pair and for each candidate set of parameters, how modal shares would change if fuel cost increased by 10%. The difference between this and the case without cost increase is summarised across the study area to derive the arc elasticity of demand to fuel cost.

Objective 4: Ensure that public transport fare elasticity in the model is within the range recommended in WebTAG.

3.28 This is implemented in a similar way to the one described for objective 3.

Objective 5: Ensure that the proportion of each components of the public transport generalised cost is within a logical range.

3.29 The market simulation tool contains a module that calculates, for each candidate parameter set, the contribution of each variable to the public transport total generalised cost. For a specific origin-destination pair, the contribution of variable K is calculated as the parameter weight of K multiplied by the value of K, divided by the total generalised cost. The equation below serves as an illustration, where K in this case is the variable In Vehicle Time (IVT) for public Transport:

Contribution of IVT to PT Gen Cost = ([IVT]*[IVT Parameter weight])/PT Gen Cost

3.30 This is summarised across all origins and destinations, and the demand in each pair is used as a weight. The idea in this calculation is to ensure that the automated model estimation process does not let the relativities between the components of the generalised public transport costs contradict our intuitive judgement. Thus, the objective here is to minimise an expression that includes a high penalty for parameter sets that make the In-Vehicle-Time constitute more than half of the total generalised cost; for parameter sets where the public transport constant is above 25% of the generalised cost; and so on.

The Downhill Simplex Method

3.31 The search for a solution for the model estimation problem used an algorithm we programmed based on the Downhill Simplex Method. This method is suitable for optimising objective functions that do not have a closed form. In our case the meta-error does not have a closed form because it depends on the parameters we estimate in an indirect way. In other words the parameters are used in a logit model to estimate modal shares for many origin-destination pairs, and the results of this estimation are aggregated in several different ways to calculate the objective values; the objective is not an explicit function of the parameters.

3.32 The Downhill Simplex Method is not a particularly efficient optimisation technique in terms of the number of iterations required to get to an optimal solution. It is also does not guarantee convergence to the global optimum. In the context of building travel demand models, a further disadvantage is that when we use this method we cannot present the statistical measures which the readers may be more familiar with, such as the Rho-squared for the full model or t-test for individual attributes.

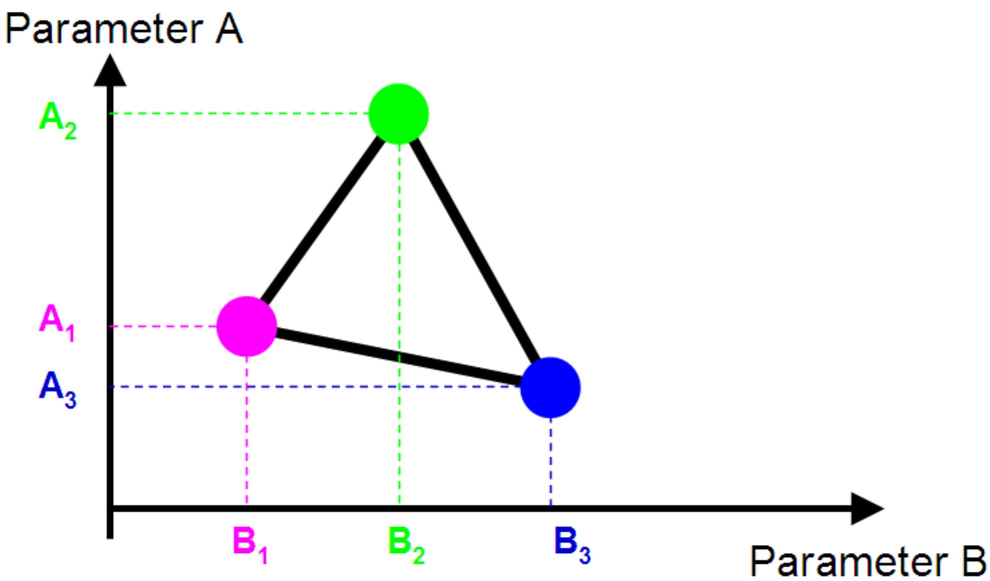
3.33 Nevertheless, this method is very powerful in that it is suitable for any type of objective function or problem, including the problem that could not be solved using a maximum likelihood approach. The Downhill Simplex Method also guarantees continuous improvement of the objective as long as we continue to allow it to run. For our current needs, using this technique appears the most robust approach available, because the alternative would be a manual trial-and-error process (which is not uncommon among practitioners).

3.34 We now describe the basics of this approach. A simplex is a geometrical shape in a multi-dimensional space. For example, a simplex in a two-dimensional space is a triangle, and a simplex in a three-dimensional space is a pyramid, but there can be simplexes in spaces of any dimension.

3.35 At each corner of a simplex there is a vertex; in a N-dimensional simplex there are N+1 vertices. When we use the Downhill Simplex Method to optimise the values of N parameters we use an N-dimensional simplex with N+1 vertices; each dimension represents one parameter and each vertex is one candidate set of values of all the parameters. The simplex at each stage of the process is the best group of candidate solutions we are aware of at that point.

3.36 A simple case, where we want to estimate a model with two parameters, is illustrated in Figure 3.4. Since there are two parameters, this is a two-dimensional problem and the simplex is a triangle. Each of the three vertices of the triangle is a possible solution of the problem. The coordinates of vertex 1, B_1 and A_1, are the respective values of parameters B and A according to solution 1; the same goes for vertices 2 and 3.

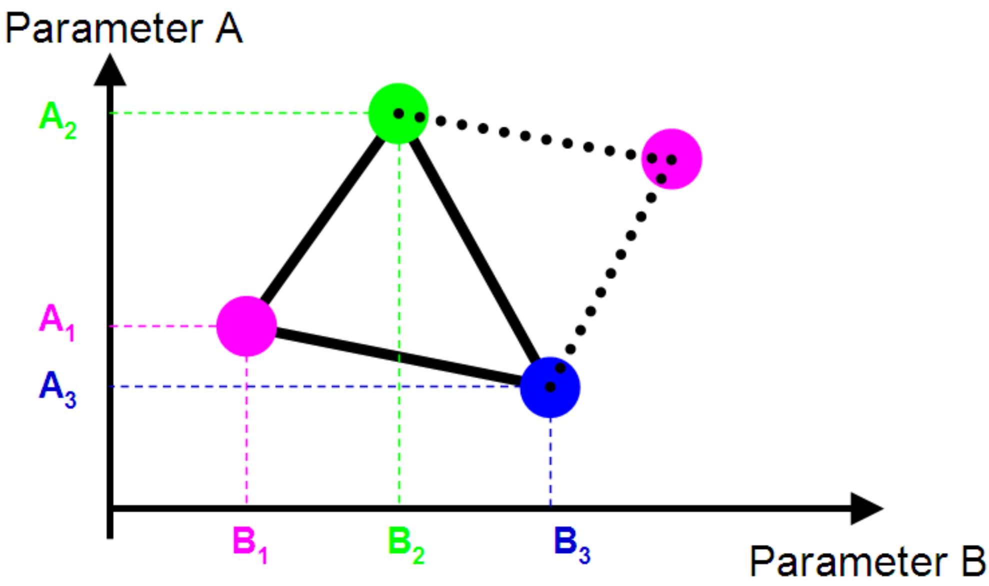
FIGURE 3.4 ILLUSTRATION OF THE DOWNHILL SIMPLEX METHOD



3.37 The fact that each vertex is a possible solution of the model estimation problem means that each vertex is in fact a Mode Choice model for which we can calculate the values of the different objectives and the meta-error. At the first stage of the Downhill Simplex algorithm we calculate the objective values for all vertices. After the first stage, we start an iterative loop, and in most iterations throughout the process the number of times we need to calculate the objective value per iteration is much smaller.

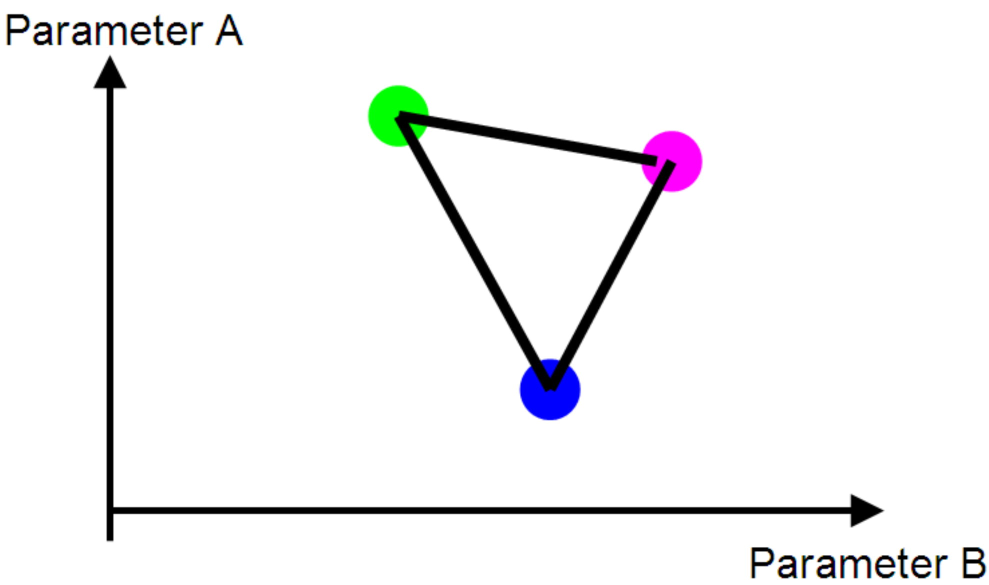
3.38 The core iterative process works as follows. Since we know the objective value (i.e. the meta-error) for each vertex, we can identify the vertex that has the worst (i.e. highest) value. We deem this “the worst vertex” and the other vertices (the remaining two, in the triangle example) “the base of the vertex”. In order to get rid of the worst vertex, and replace it with a better solution of our problem, we undertake a reflection manoeuvre. Namely, we replace the worst vertex with a point in space that lies at the same distance from the base of the simplex as the worst vertex, but on the opposite side of the base. If vertex 1 in Figure 3.4 was the worst vertex, Figure 3.5 demonstrates how we undertake a reflection manoeuvre.

FIGURE 3.5 ILLUSTRATION OF THE DOWNHILL SIMPLEX METHOD



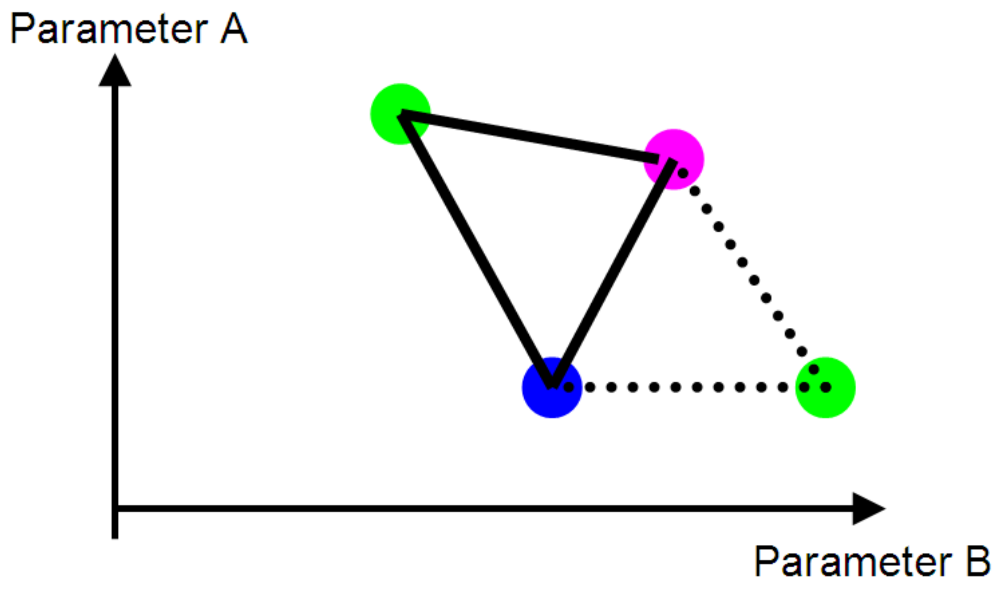
3.39 It is merely a guess that the new vertex, with the implied new values of the parameters, would have a better value of the objective; but this is an intelligent guess which often works well. If the objective in the new location is indeed better than the worst objective value in the original simplex, we complete this manoeuvre and we now have a new simplex, as described in Figure 3.6.

FIGURE 3.6 ILLUSTRATION OF THE DOWNHILL SIMPLEX METHOD



3.40 Like any simplex, one of the vertices in the new simplex is "the worst vertex", and with it we can start a new iteration. Figure 3.7 illustrates what the next reflection might be like. We can do this repetitively until we are satisfied with the objective value we reach. It is worth noting that although in each iteration we improve the worst vertex of the simplex, when we decided to halt this process it is sensible to use the best vertex.

FIGURE 3.7 ILLUSTRATION OF THE DOWNHILL SIMPLEX METHOD



3.41 The reflection manoeuvre does not work well in every iteration. If a simple reflection does not lead to an improved objective value, some alternative types of reflection are investigated. We avoid a full description of all technical aspects of this process here, but these are available from our team, or in the optimisation literature, if necessary.

3.42 The model estimation discussed in this report has more parameters than in the example above, and therefore the solution is not as graphically intuitive. Nevertheless, the principles of the process as the same. We have run this algorithm separately with the commuting trips dataset and with the dataset of other journeys, and in each of these we reached a set of parameter values from which it appeared that no further improvement of the meta-error was possible. These models are presented in the next chapter.

4. TIME OF TRAVEL & MODE CHOICE CALIBRATION RESULTS

Introduction

4.1 In this chapter we present the results of the Time of Travel and Mode Choice Calibration. The calibration process began with estimating parameter values for each cost components in the Time of Travel Choice model (as detailed in Chapter 2). The parameter values were then used within a logsum function in order to produce composite costs by mode which fed into the Mode Choice process. The Mode Choice calibration involved estimating mode constants and scaling parameters and once these were finalised, they too were used in a logsum function in order to produce composite costs for each OD pair across the entire AM peak period and across all three modes (highway, PT and slow mode (SM – i.e. walk and cycle). A summary of the estimated parameters is shown in Table 4.1 and Table 4.2.

4.2 The calibration process began with the current hierarchical structure as outlined on page 4, however it was not limited to this form. The scaling parameters of the higher and lower nests were given sufficient freedom to vary. Indeed there were instances where the two scaling parameters were found to be equal to one another and in these cases the structure of model was considered to have reverted to that of the Multinomial Logit model (i.e. a flat structure with no intermediate nests). Note that in these instances, the estimated parameter values were still quoted in their hierarchical form for operational ease of use. This does not impact on the application of these parameters; it is merely a matter of interpretation.

4.3 The remainder of this chapter presents the results of the Goodness of Fit tests and Realism tests for the calibration of the Commute or Home to Work journey purpose. The actual parameter values derived from this exercise are contained within Appendix A. The results of the tests for the other five journey purposes are included within Appendix B.

TABLE 4.1 SUMMARY OF ESTIMATED PARAMETERS: MODE CHOICE

Parameter	Applies to Segment:
PT Mode Constant	Car Available Trips
Mechanised Mode Constant	Car Available Trips
Scaling Parameter	Car Available Trips
Mechanised Mode Scaling Parameter	Car Available Trips
PT Mode Constant	Car Non-Available Trips
Scaling Parameter	Car Non-Available Trips

TABLE 4.2 SUMMARY OF ESTIMATED PARAMETERS – TIME OF TRAVEL CHOICE

Parameter	Applies to Mode:
Distance (7am – 8am)	Highway
Distance (8am – 9am)	Highway
Distance (9am – 10am)	Highway
Travel Time (7am – 8am)	Highway
Travel Time (8am – 9am)	Highway
Travel Time (9am – 10am)	Highway
Toll (7am – 8am)	Highway
Toll (8am – 9am)	Highway
Toll (9am – 10am)	Highway
Walk (7am – 8am)	Public Transport
Walk (8am – 9am)	Public Transport
Walk (9am – 10am)	Public Transport
In Vehicle Time (7am – 8am)	Public Transport
In Vehicle Time (8am – 9am)	Public Transport
In Vehicle Time (9am – 10am)	Public Transport
Wait Time (7am – 8am)	Public Transport
Wait Time (8am – 9am)	Public Transport
Wait Time (9am – 10am)	Public Transport
Transfer (7am – 8am)	Public Transport
Transfer (8am – 9am)	Public Transport
Transfer (9am – 10am)	Public Transport
Fare (7am – 8am)	Public Transport
Fare (8am – 9am)	Public Transport
Fare (9am – 10am)	Public Transport
Crowding (7am – 8am)	Public Transport
Crowding (8am – 9am)	Public Transport
Crowding (9am – 10am)	Public Transport
Alternative Specific Constant (8am – 9am)	Public Transport
Alternative Specific Constant (7am – 9am)	Public Transport
Scaling Parameter	Public Transport
PT Scaling Parameter	Public Transport

4.4 The toll and fare parameters were estimated using VOT values sourced from the 2004 GEC report *(Parameter Values for Use in Cost-Benefit Analysis of Transport Projects, Goodbody Economic Consultants in association with Atkins - Sep 2004)*. For non-business trips, the VOT value used was 8.1 Euro/person/hour. For business trips, the VOT value used was 26.5 Euro/person/hour. These values, expressed in 2002 prices, were inflated by 4% per annum in order to derive VOT values in 2006 prices of 9.48 Euro/ person/ hour (non-business trips) and 31.00 Euro/ person/ hour (business trips).

4.5 The 2006 VOT values were multiplied by a calibration parameter in order to arrive at the toll and fare parameters listed in table 4.2. The calibration parameter values were derived during the calibration process. The process of selecting appropriate values for these parameters was the same as with all the other parameter values as discussed in paragraphs 3.14 to 3.30.

Commute (Home to Work) Results

4.6 The following charts present the results of the calibration process for Commute trips. The format of these charts is as follows:

- Time of Travel Choice Goodness of Fit and Realism Tests;
  - Highway Demand: Observed v Modelled at an Aggregate Level
  - Highway Demand by Time Period: Observed v Modelled at OD Pair level
  - Highway Implied Elasticities by Time Period: Fuel costs and Travel Time
  - PT Demand: Observed v Modelled at an Aggregate Level
  - PT Demand by Time Period: Observed v Modelled at OD Pair level
  - PT Implied Elasticities by Time Period: Fuel costs and Travel Time

- Mode Choice Goodness of Fit and Realism Tests;
  - Car Available Demand: Observed v Modelled at an Aggregate Level
  - Car Available Demand by Mode: Observed v Modelled at OD Pair level
  - Car Non Available Demand: Observed v Modelled at an Aggregate Level
  - Car Non Available Demand by Mode: Observed v Modelled at OD Pair level
- Geographical Analysis of Composite Costs by Zone to a specific destination.

4.7 For each scatter chart which shows the observed versus modelled demand at OD pair level, we have derived a measure of goodness of fit referred to as the Root Mean Squared Weighted Error or RMSWE. This measure is weighted to reflect the fact that demand differs per OD pair and the squared element has the effect of a) placing equal weight on positive and negative differences as well as b) heavily penalising large differences between observed and modelled.

Interpretation of RMSWE

4.8 There are no clear RMSWE ranges which define when model fit is “good”, “reasonable” or “poor”. It can be shown that the lower the RMSWE value, the lower the error associated with the model, and hence the better the fit. The following tables serve to illustrate this point.

4.9 In Table 4.3, the modelled demand is almost the same as the observed demand across all OD pairs. The result is a RMSWE very close to zero. Note, by definition, the RMSWE cannot take on a value below zero.

TABLE 4.3 RMSWE: EXAMPLE OF A GOOD FITTING MODEL

OD Pair	Modelled	Observed	Error
1-2	12	13	0.077
1-3	15	14	0.071
1-4	34	33	0.030
1-5	68	69	0.014
2-3	74	75	0.013
2-4	33	34	0.029
2-5	57	56	0.018
3-4	44	43	0.023
3-5	20	19	0.053
4-5	39	40	0.025
Overall	396	396	0.355
		RMSWE=	**0.030**

4.10 Table 4.4 shows a worked example of a poor fitting model. It can be seen that there is very little similarity between the modelled and observed values and virtually no correlation between the two sets of figures. This results in a RMSWE close to 2. Thus broadly, we consider RMSWE values in the range of 0 to 2 to be "reasonable" with values close to zero particularly "good" and those approaching 2, poorer in nature.

TABLE 4.4 RMSWE: EXAMPLE OF A POOR FITTING MODEL

OD Pair	Modelled	Observed	Error
1-2	12	106	83.358
1-3	15	128	99.758
1-4	34	3	320.333
1-5	68	80	1.800
2-3	74	22	122.909
2-4	33	2	480.500
2-5	57	9	256.000
3-4	44	143	68.538
3-5	20	99	63.040
4-5	39	2	684.500
Overall	396	594	2180.738
		RMSWE=	**1.916**

4.11 There are instances where the reported RMSWE is considerably greater than 2, and can at times reach three figures. This is attributed to the way the error measure is formulated. Models containing a very low observed frequency of trips per OD pair (i.e. less than 1) can produce very large RMSWE values. In these circumstances, it is not necessarily the case that the goodness of fit is poor, rather the low frequency of observed trips, with forms the denominator in the RMSWE formula, is inflating the statistic. An example of this is shown in the Table 4.5.

TABLE 4.5 RMWSE: EXAMPLE WITH VERY LOW OBSERVED VALUES

OD Pair	Modelled	Observed	Error
1-2	0.3	0.054005	1.121
1-3	0.03	0.010136	0.039
1-4	0.07	0.050948	0.007
1-5	0.05	0.015943	0.073
2-3	0.03	0.003564	0.196
2-4	0.06	5.31E-05	67.694
2-5	0.098	0.010409	0.737
3-4	0.06	0.050908	0.002
3-5	0.09	0.037398	0.074
4-5	0.07	0.01401	0.224
Overall	0.858	0.247373	70.166
		RMSWE=	**16.842**

4.12 In Table 4.5, the observed values by OD pair are all below one and the observed value for OD pair 2-4 is very close to zero. This value forms the denominator in the error function and this has resulted in a greatly inflated error value (67.694). The net result is an RMSWE of 16.842, far outside the suggested 0 – 2 range.

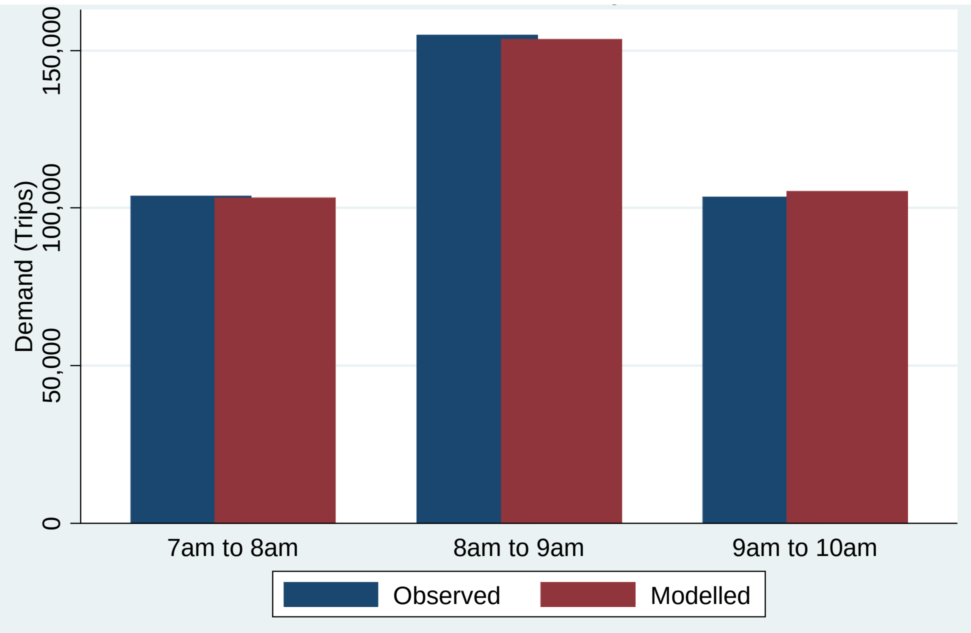
4.13 To maintain a consistent reporting format, we report the RMSWE statistic for all models. However, where the value is greater than 2 this is likely to be due to the presence of very low observed counts in a number of OD pairs. In these instances we would recommend the reader focuses on the alternative performance indicators reported such as the scatter plots of observed v modelled demand, and the overall percentage error as shown by the bar charts of overall observed v modelled demand.

4.14 Alternative measures of goodness-of-fit exist. One common measure is the GEH statistic. However, this measure is only applicable to highway flows. Its application to PT flows is inappropriate as it will always tend to report a satisfactory level of fit when used in these circumstances. The use of the RMSWE measure is therefore considered a more rigorous test. In addition to this, when we calibrate a model, we take into consideration of a suite of measures which include RMSWE along with the overall percentage error, the implied elasticities and also, of no less importance, the intuitiveness of the parameter values (i.e. their sign and magnitude).

Time of Travel Choice: Highway Results

4.15 Overall the calibration achieved a reasonable fit across all three time bands at an aggregate level.

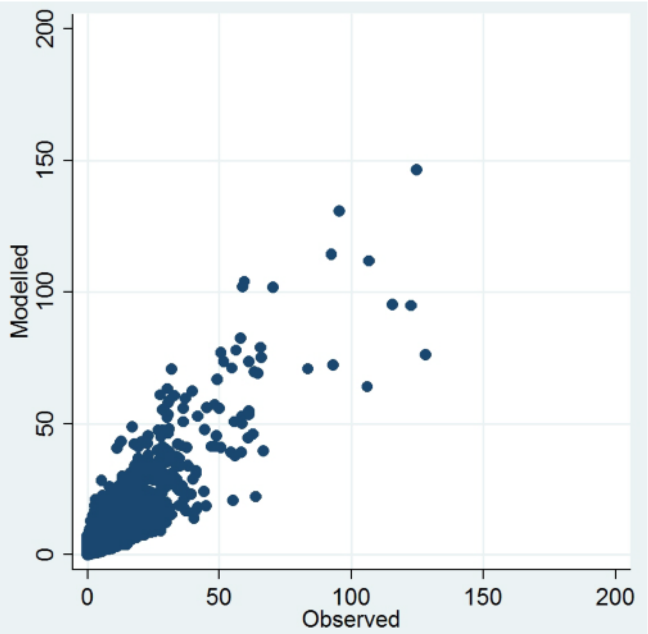
FIGURE 4.1 HIGHWAY DEMAND: MODELLED V OBSERVED BY ARRIVAL TIME



Highway Results 7AM-8AM

4.16 Each point in Figure 4.2 refers to an individual OD pair. The extent to which these points lie on a 45 degree line from the origin indicates how well the model fits the observed data at this level; the greater the dispersion away from a 45 degree line, the greater the amount of forecast error in the estimated parameters.

FIGURE 4.2 HIGHWAY DEMAND (7AM -8AM): MODELLED V OBSERVED BY OD



Root Mean Squared Weighted Error (RMSWE) = 2.987

4.17 No model will perfectly predict reality so the 45 degree line is a theoretical ideal rather than an expectation. However, the scatter chart can help to identify the worst type of calibration; that where the points lie on, or very close to the x and y axis indicating no relationship between the observed value and modelled value.

4.18 The large RMSWE value obtained from Figure 4.2 (2.987) is attributed to the significant proportion of OD pairs with very low (near zero) observed demand. This is illustrated in Table 4.6 below.**Error! Reference source not found.**

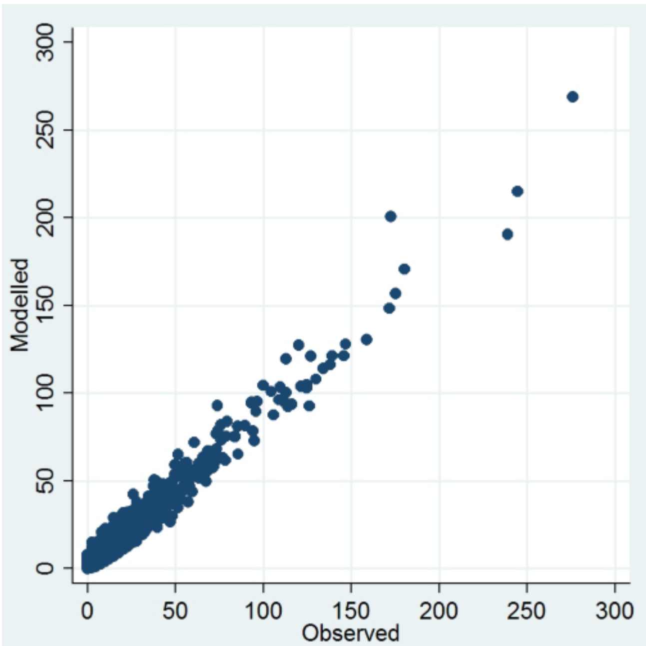
TABLE 4.6 DISTRIBUTION OF OBSERVED DEMAND BY OD PAIR (7AM-8AM)

Distribution Measure	Observed Demand (7AM-8AM)
Lowest	0.000
1st Percentile	0.000
25th Percentile	0.001
50th Percentile	0.015
75th Percentile	0.642
95th Percentile	2.811
Largest	128.126

4.19 At least 75% of OD pairs have an observed demand of less than one trip. Recall that in the RMSWE equation, the observed demand forms the denominator; as such, when this value is close to zero it greatly inflates the RMSWE measure.

Highway Results 8AM-9AM

FIGURE 4.3 HIGHWAY DEMAND (8AM-9AM): MODELLED V OBSERVED BY OD



RMSWE = 2.701

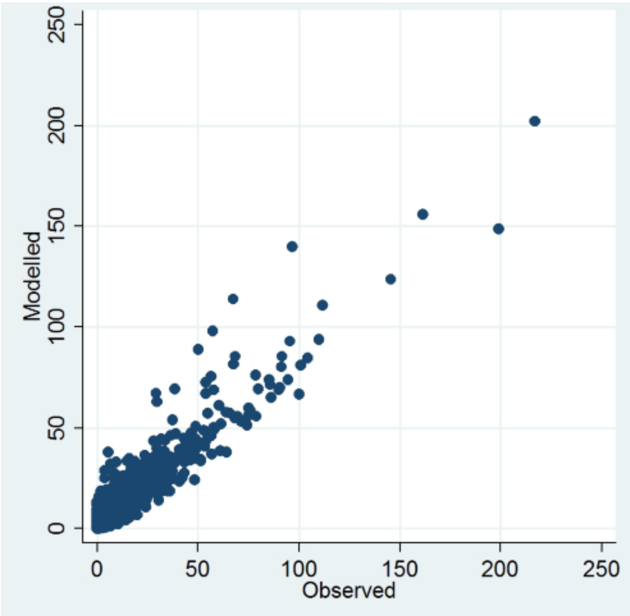
4.20 The high RMSWE obtained from the data in the 8AM to 9AM time band, shown in Figure 4.3, can once again be attributed to the high proportion of OD pairs with observed demand very close zero. In Table 4.7, 75% of all OD pairs in this time band have observed demand of less than one trip.

TABLE 4.7 DISTRIBUTION OF OBSERVED DEMAND BY OD PAIR (8AM - 9AM)

Distribution Measure	Observed Demand (8AM-9AM)
Lowest	0.000
1st Percentile	0.000
25th Percentile	0.001
50th Percentile	0.033
75th Percentile	0.942
95th Percentile	3.748
Largest	275.926

Highway Results 9AM-10AM

FIGURE 4.4 HIGHWAY DEMAND (9AM-10AM): MODELLED V OBSERVED BY OD



RMSWE = 3.195

4.21 There is a high proportion of OD pairs with very low observed demand (75% less than one trip). This leads to the high RMSWE value shown in Figure 4.4.

TABLE 4.8 DISTRIBUTION OF OBSERVED DEMAND BY OD PAIR (9AM - 10AM)

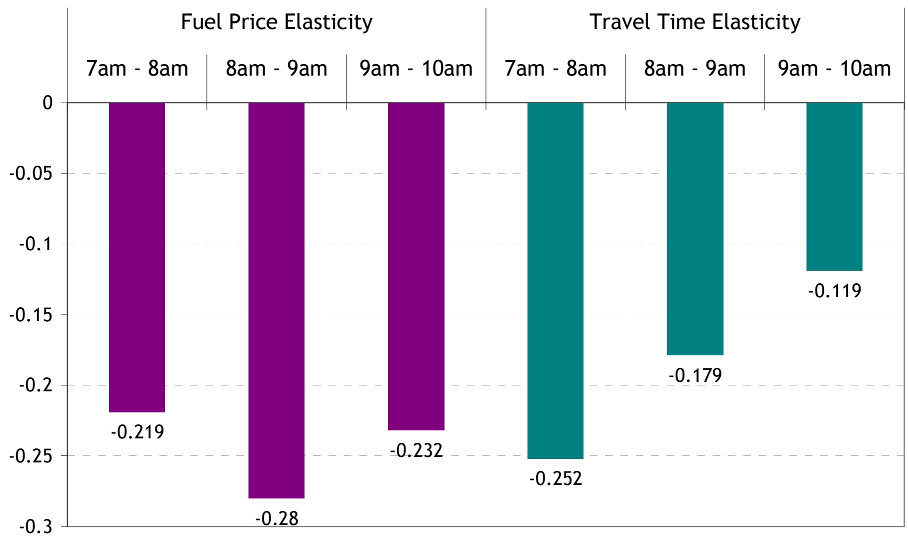
Distribution Measure	Observed Demand (9AM-10AM)
Lowest	0.000
1st Percentile	0.000
25th Percentile	0.001
50th Percentile	0.017
75th Percentile	0.850
95th Percentile	2.598

Distribution Measure	Observed Demand (9AM-10AM)
Largest	216.920

4.22 In general, the three scatter plots show a good degree of association between the observed values and modelled values of highway demand at an OD pair level. This is particularly prevalent in the 8am to 9am period (in this chart there is less dispersion) as this category has the majority share of the demand (see Figure 4.1). Generally, the greater the amount of data used to estimate the parameters, the greater the degree of model fit.

4.23 With a set of estimated parameters it is possible to obtain implied fuel price and travel time elasticities from the highway model. This is done by applying a small incremental percentage increase in the Distance cost element (for fuel price elasticity) or Time cost element (for travel time elasticity) of the generalised cost function and then feeding this through the logit function in order to determine the new proportions of demand.

FIGURE 4.5 ELASTICITY VALUES IMPLIED BY THE HIGHWAY MODEL



4.24 There are published sources available of reference elasticities by mode. In the UK, Webtag (the Department for Transport's reference website) suggests fuel price elasticities to be in the region of -0.1 to -0.4. Although, it is noted that values will vary depending on journey purpose, with discretionary trips (e.g. leisure, shopping) incurring a more negative elasticity than trips to work, education or on business.

4.25 In Figure 4.5 we note the fuel price elasticities for highway commuting trips to be between -0.22 and -0.28. This is in line with the reference material. The guidance on travel time elasticity is less well defined. Webtag advises that such values should be checked and where they exceed -2.0, the models should be re-checked in case of error. The travel time elasticities implied by this model are all well within his threshold and so we consider this model to have passed these realism tests.

Time of Travel Choice: Public Transport Results

4.26 The calibrated PT model provides a good level of fit at an aggregate level (i.e. across all zones). Once again, the modal arrival group is the 8am – 9am period.

FIGURE 4.6 PT DEMAND: MODELLED V OBSERVED BY ARRIVAL TIME

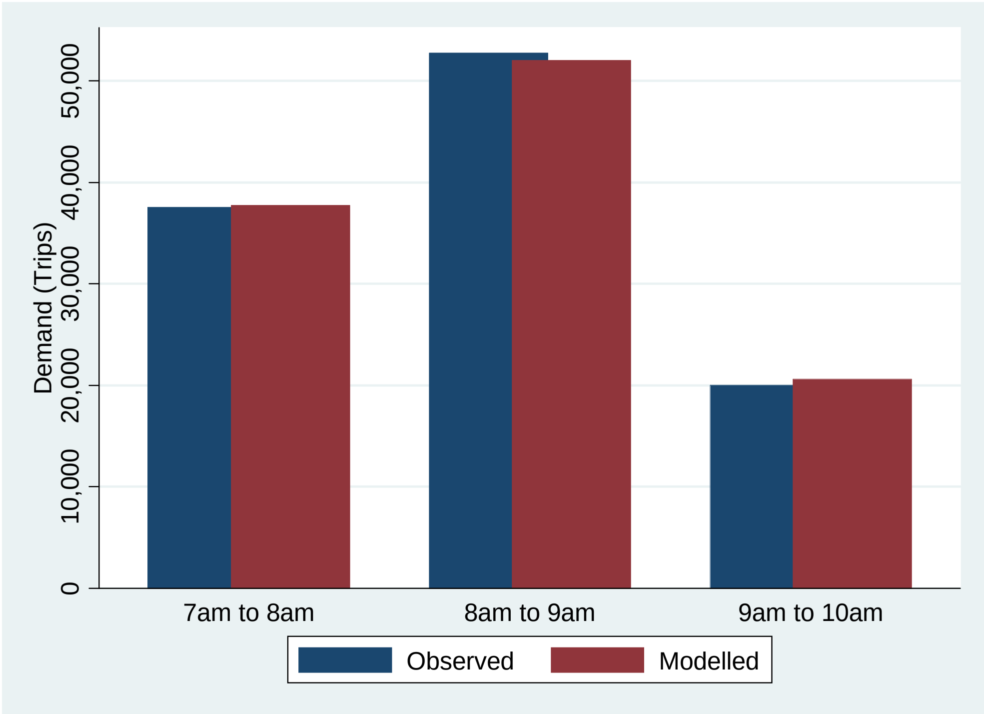
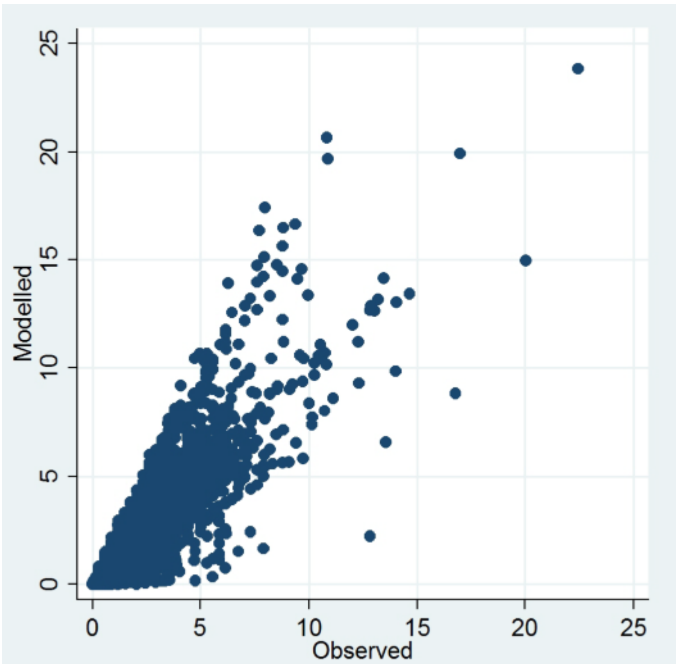


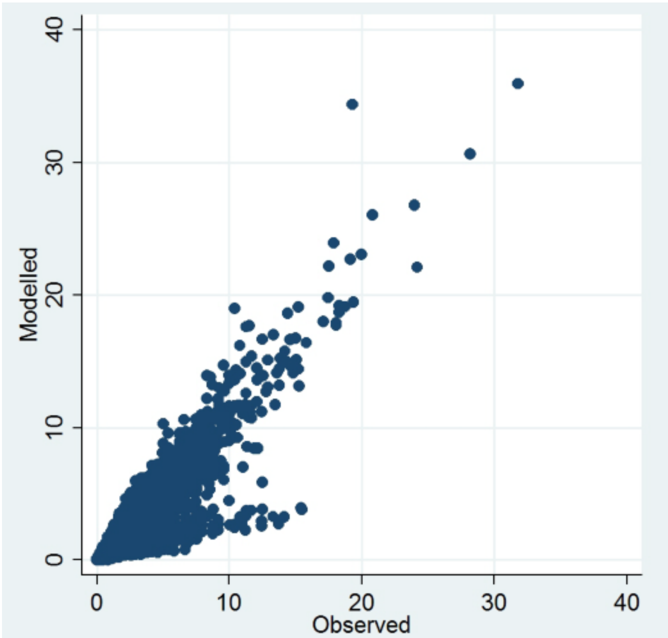
FIGURE 4.7 PT DEMAND (7AM - 8AM): MODELLED V OBSERVED BY OD PAIR



RMSWE = 0.355

4.27 In Figure 4.7 the points, which represent individual OD pairs, are clustered in and around the 45 degree line indicating a reasonable level of fit at this level. This is further supported by the very low RMSWE value of 0.355.

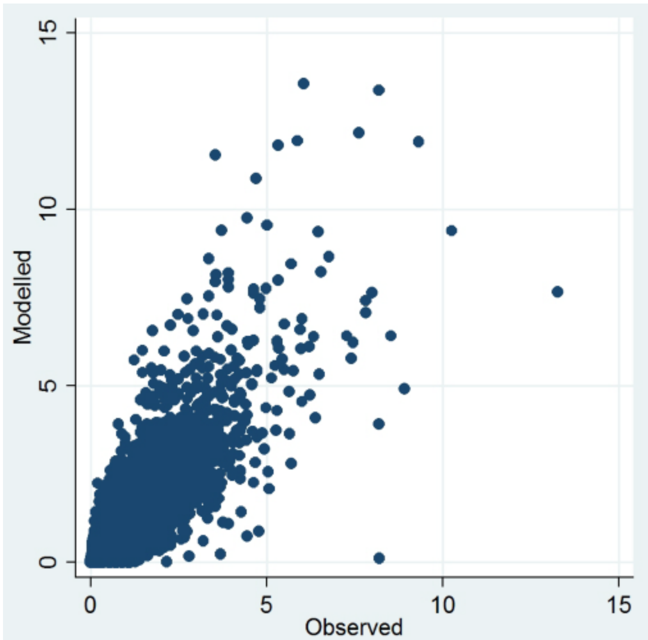
FIGURE 4.8 PT DEMAND (8AM - 9AM): MODELLED V OBSERVED BY OD PAIR



RMSWE = 0.266

4.28 In Figure 4.8 the points form a tighter cluster around the 45 degree line and a lower value of RMSWE when compared with the 7am – 8am time band. This is attributed in part to the fact that there are a greater number of trips made in the 8am to 9am period which contributes to an increased goodness of fit.

FIGURE 4.9 PT DEMAND (9AM - 10AM): MODELLED V OBSERVED BY OD PAIR



RMSWE = 0.546

4.29 In Figure 4.9, the dispersion of points is greater than that seen in the previous two scatter plots. The RMSWE value is also higher indicating a slight deterioration in model fit when compared with the previous two plots. The “commuting” journey purpose category is made up of home to work as well as work to home trips. The return journeys were combined with the outward journeys as there were not enough of them to model separately. The 9am to 10 am period contains the greatest proportion of return trips (i.e. WtoH) and it may be these trips, with different characteristics to the outward trips, which are contributing towards the ‘cloud’ effect seen in Figure 4.9. Despite this, the plot still shows an underlying scattering of points around a theoretical 45 degree line and so we deem the model to have passed this test.

FIGURE 4.10 ELASTICITY VALUES IMPLIED BY THE PT MODEL

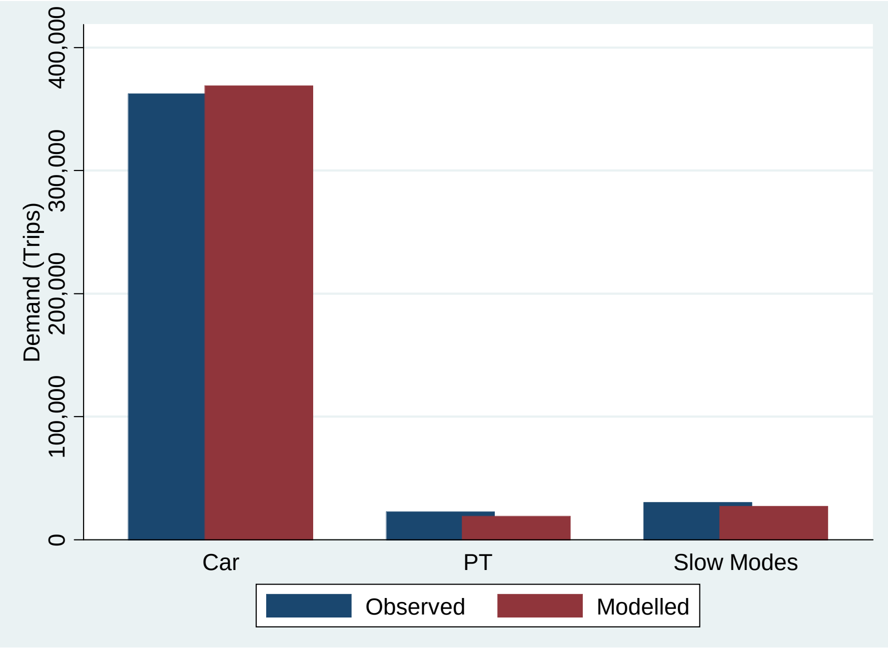
4.30 The implied fare price elasticities for PT commuting trips are very low (between -0.05 and -0.078). This appears reasonable given that a large proportion of PT commuting trips are made by travellers with no access to a car, and so not available alternative to switch from PT (the average proportion of PT trips where a car is available, across all 666 DTO zones, is 0.21 source: DTO AM Car Availability proportions April 2009). The implied travel time elasticities are also well within the suggested range proposed by Webtag (i.e. less than -2.0).

Mode Choice Results – Car Available Travellers

4.31 A nested logit function is used to model the choices made by travellers who have access to a car. There are three options available; car, PT and slow mode (walk and cycle). The nested structure consists of a Mechanised Mode (MM) nest v Slow Mode at the higher level. The MM nest is further broken down into PT v car at the lower level (see Figure 2.1, page 4). The calibration involves estimating two scaling parameters (one scaling parameter for the MM nest and one at the higher level) and two Alternative Specific Constants (one within the MM nest (PT) and at the higher level associated with MM itself).

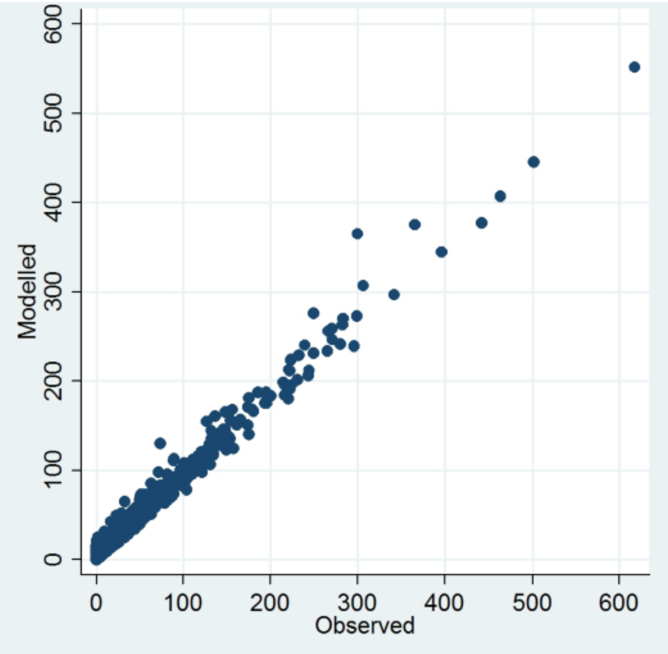
4.32 In this section we present the results of a series of Goodness-of-Fit tests following the calibration exercise.

FIGURE 4.11 CAR AVAILABLE COMMUTING DEMAND: MODELLED V OBSERVED BY MODE



There is a good fit between modelled and observed demand at an aggregate level as shown in Figure 4.11. It is evident that Car is the dominant mode accounting for 86% of demand (this is shown in Table 4.9 in section 4). In models where one alternative makes up such a large proportion of the overall demand it is often the case that at an OD level, a very good level of fit is achieved for that alternative and very poor fit for the other alternatives. This is shown to some extent in the following scatter plots.

FIGURE 4.12 CAR AVAILABLE COMMUTING TRIPS (MODE=CAR): MODELLED V OBSERVED BY OD PAIR

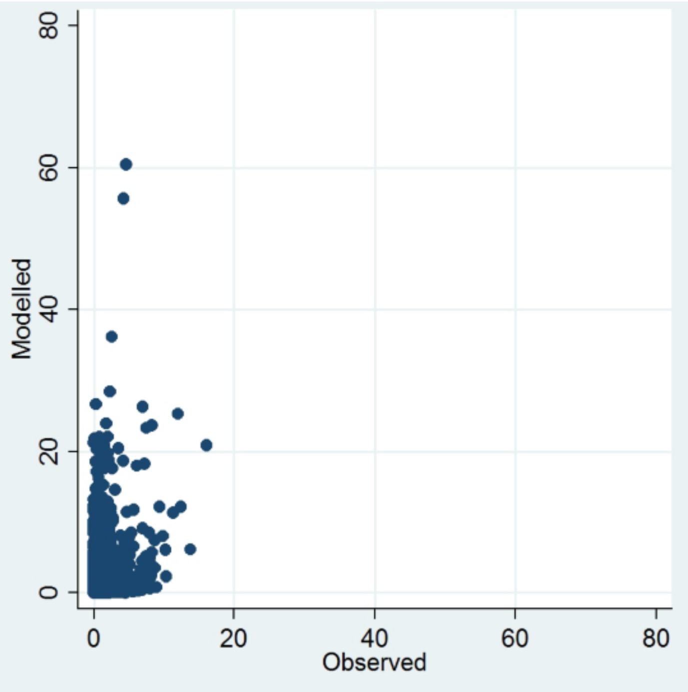


RMSWE = 1.138

4.33 An impressive goodness of fit is achieved for car trips. This is not surprising given car's dominance in terms of proportion of overall trips when compared to the other modes. However, there is still a significant proportion (at least 50%) of OD pairs with observed demand less than one which results in an inflated RMSWE value of 1.138.

4.34 The goodness of fit achieved for PT trips is relatively poor in comparison to the car trips in Figure 4.12.

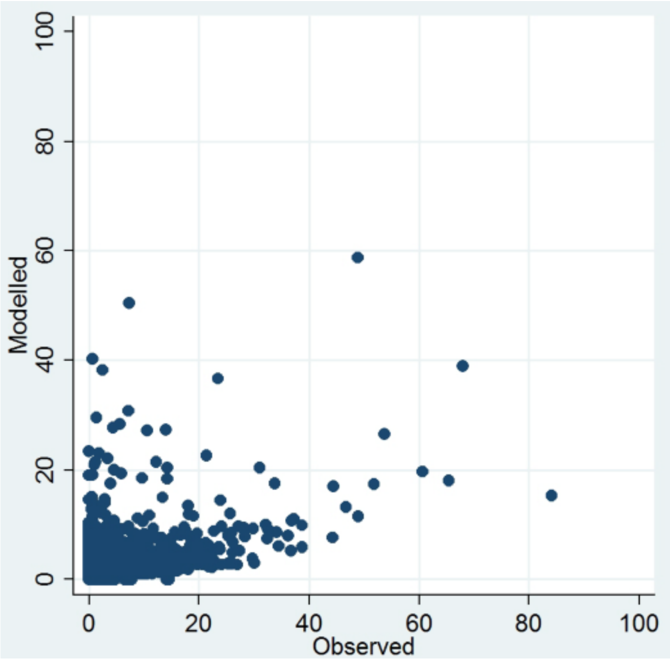
FIGURE 4.13 CAR AVAILABLE COMMUNTING TRIPS (MODE=PT): MODELLED V OBSERVED BY OD PAIR



RMSWE = 3.364

The calibration was re-run a number of times, altering the parameter estimates each iteration in an attempt to improve the scatter plot, Figure 4.13 represents the best outcome. Whilst it is far from ideal (there is a skew towards the y axis and a large RMSWE caused by a very large proportion of OD pairs with very low observed demand (90% of OD pairs with demand of 0.23 trips or less), it does achieve a reasonable fit at least for a proportion of the OD pairs, and with the exception of three outliers, the difference between modelled and observed is within tolerable limits. Unfortunately, with such a low proportion of car-available, PT commuting trips, the poor fit observed in Figure 4.13 is somewhat unavoidable.

FIGURE 4.14 CAR AVAILABLE COMMUTING TRIPS (MODE=SLOW MODE): MODELLED V OBSERVED BY OD PAIR



RMSWE = 5.163

4.35 The goodness of fit observed for slow mode commuting trips in Figure 4.14 is an improvement on that seen for PT trips. There is some degree of match between modelled and observed. This is because slow mode trips make up a larger proportion of all trips compared to PT. Despite this, the RMSWE is significantly higher at 5.163. This is attributed to that fact that 95% of OD pairs have less than one observed trip.

4.36 It should be noted that plotting the scatter charts at individual OD pair level provides the most rigorous of tests and had the plots been constructed at a sector level, as is often the case in such performance testing, it is likely that the results obtained would be have appeared far more reasonable.

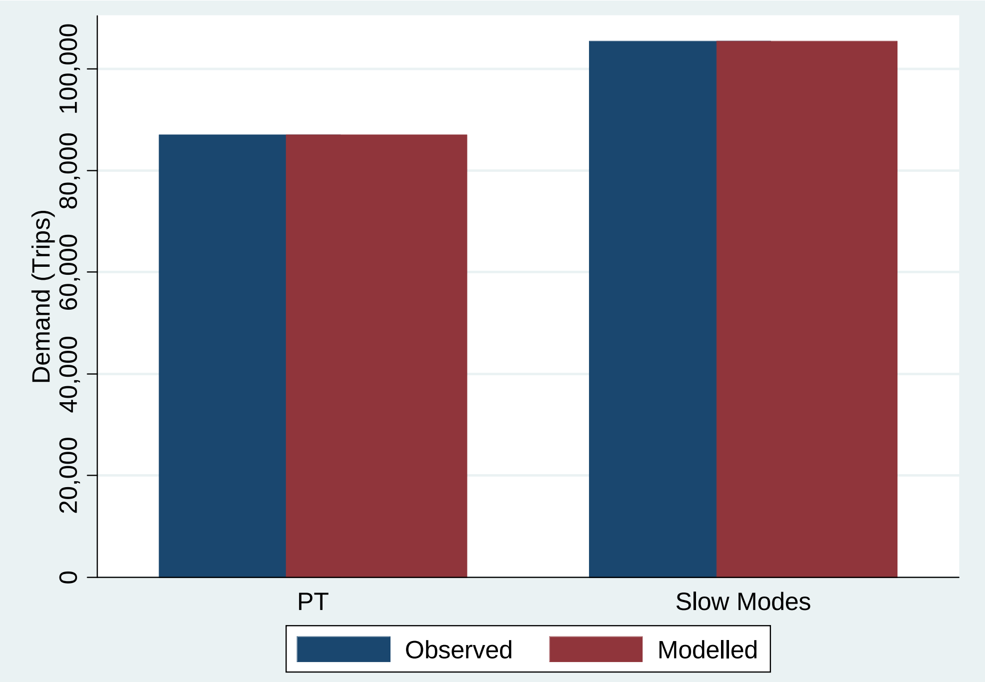
Mode Choice Results – Car Non-Available (CNA) Travellers

4.37 A multinomial logit function is used to model the choices made by travellers whom have no access to a car. There are two options available to this group; PT or slow mode.

4.38 The calibration of the CNA model involved estimating parameter values for a scaling parameter and a mode constant (PT).

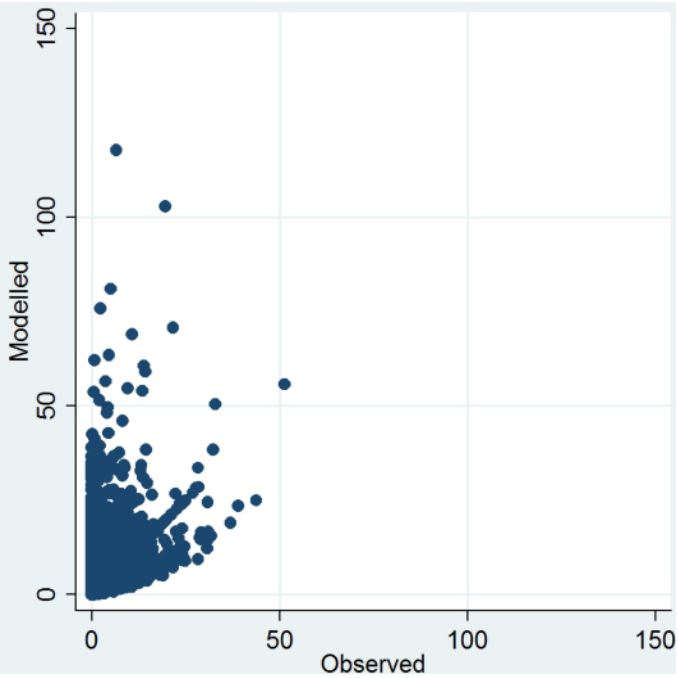
4.39 In this section, we present the results of a set of Goodness-of-Fit tests following the calibration of the CNA model.

FIGURE 4.15 CNA COMMUTING DEMAND: MODELLED V OBSERVED BY MODE



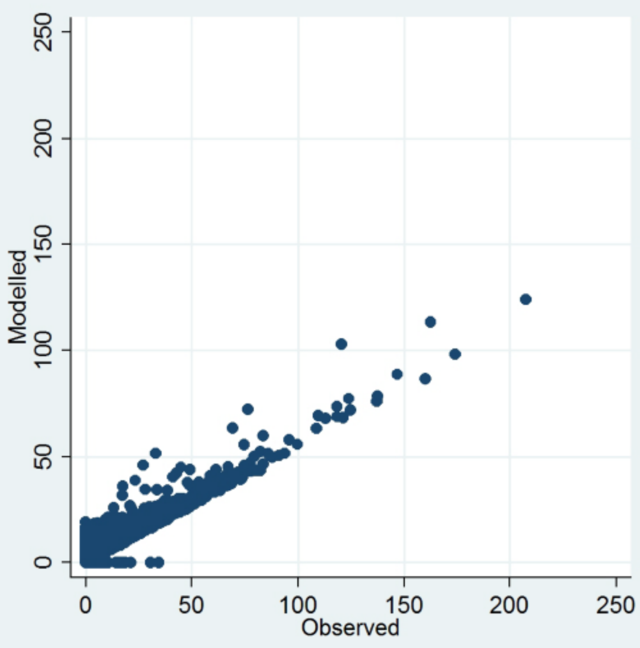
4.40 A good level of model fit was achieved at the aggregate level (i.e. across all OD pairs).

FIGURE 4.16 CNA COMMUTING DEMAND (MODE=PT): MODELLED V OBSERVED BY OD PAIR



RMSWE = 2.771

FIGURE 4.17 CNA COMMUTING TRIPS (MODE=SLOW MODE): MODELLED V OBSERVED BY OD PAIR



RMSWE = 3.480

4.41 At an individual OD level, a reasonable goodness of fit was achieved for slow modes (Figure 4.17 shows a clear '45 degree cloud' of points). A RMSWE value of 3.480 was obtained. This is as a result of a large proportion of OD pairs with very low demand (75% of OD pairs of less than 0.01 observed trips). The model fit for PT trips was less good (Figure 4.16). As the calibration process involves estimating just two parameters (scaling parameter and mode constant), there are fewer degrees of freedom available to produce a tighter fit across both modes. Nevertheless, Figure 4.16 does show a large proportion of OD pairs in and around the 45 degree theoretical line and so we deem this amount of variability in the scatter plot to be within tolerance. A RMSWE value of 2.771 was observed from the data from figure 4.16 and once again we note a very high proportion of OD pairs with very low observed demand which is driving this.

Composite Costs

4.42 The Time of Choice and Mode Choice model calibration results in a set of estimated parameter values (listed in Appendix A Tables). The parameter values are applied to the input costs from both models in order to arrive at a set of composite costs. The composite costs combine all three time periods and all three forms of mode and are used to inform the Trip Distribution stage on the overall cost of travelling from any origin zone to any destination zone during the AM peak.

4.43 Analysis of the resultant composite costs indicated a significant proportion of negative values. This is not cause for concern as the 'logsumming' process tends to make costs smaller and negative. Applying a constant to all composite costs is permissible if the resultant composite costs are to be used in a logit function (as adding a constant does not change the relativities in the exponents). In light of this, a constant of 1000 was applied to all costs in order to convert them all into positive numbers.

4.44 The final stage involved obtaining costs for intra-zonal journeys. During the network phase, skims were not obtained for intra-zonal journeys and so these costs were estimated upon completion of the mode choice calibration. For each origin zone, the minimum cost to all other zones was obtained. The intra-zonal cost for each zone was then estimated to be 50% of this minimum cost value.

4.45 A series of checks were undertaken on the composite costs to ensure they made intuitive sense. In Figure 4.18 the composite costs of commuting to the airport are shown for all zones. Note, the destination zone is shown outlined in dark blue. The zones closest to the destination zone are shaded in lighter colours to indicate lower costs. As you look further out, away from the destination zone, the zones are shaded progressively darker colours, indicating increased costs. This is in line with expectations as composite costs are a function of travel distance and travel time.

4.46 Composite costs for Car Non-Available commuting trips to the airport are shown in Figure 4.19. In this map, the general pattern of lighter colours nearest the destination zone and darker colours furthest from the destination zone is again observed. However, there are also pockets or "islands" of lighter coloured zone clusters further out from the destination zone (most notably in the region south west of Naas). The lighter coloured zones here indicate lower composite costs due to the availability of rail stations (represented by red circles) in the local area. This is also shown along the coast between Bray and Wicklow, where lighted coloured zones are found near rail stations.

4.47 In summary, the composite costs produced following the calibration are considered intuitively sensible. Observations of the costs from the geographical analysis can be explained either in terms of locality to destination or, in the case of non-car available trips, locality to connecting services. A number of maps, similar to those presented in Figure 4.18 and Figure 4.19 have been produced and these are included within Appendix A.

FIGURE 4.18 COMPOSITE COSTS - COMMUTE CAR AVAILABLE TRIPS TO AIRPORT

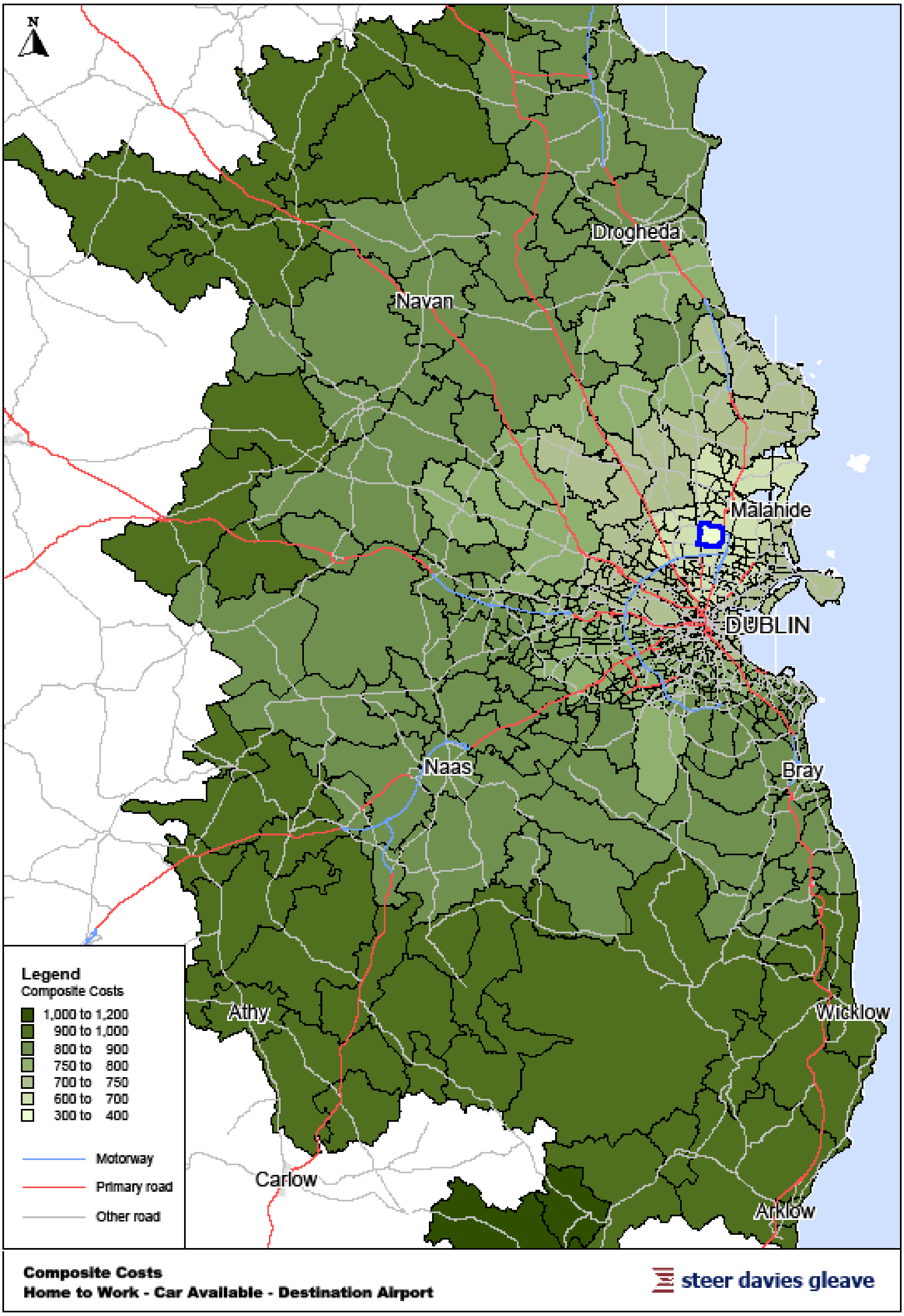
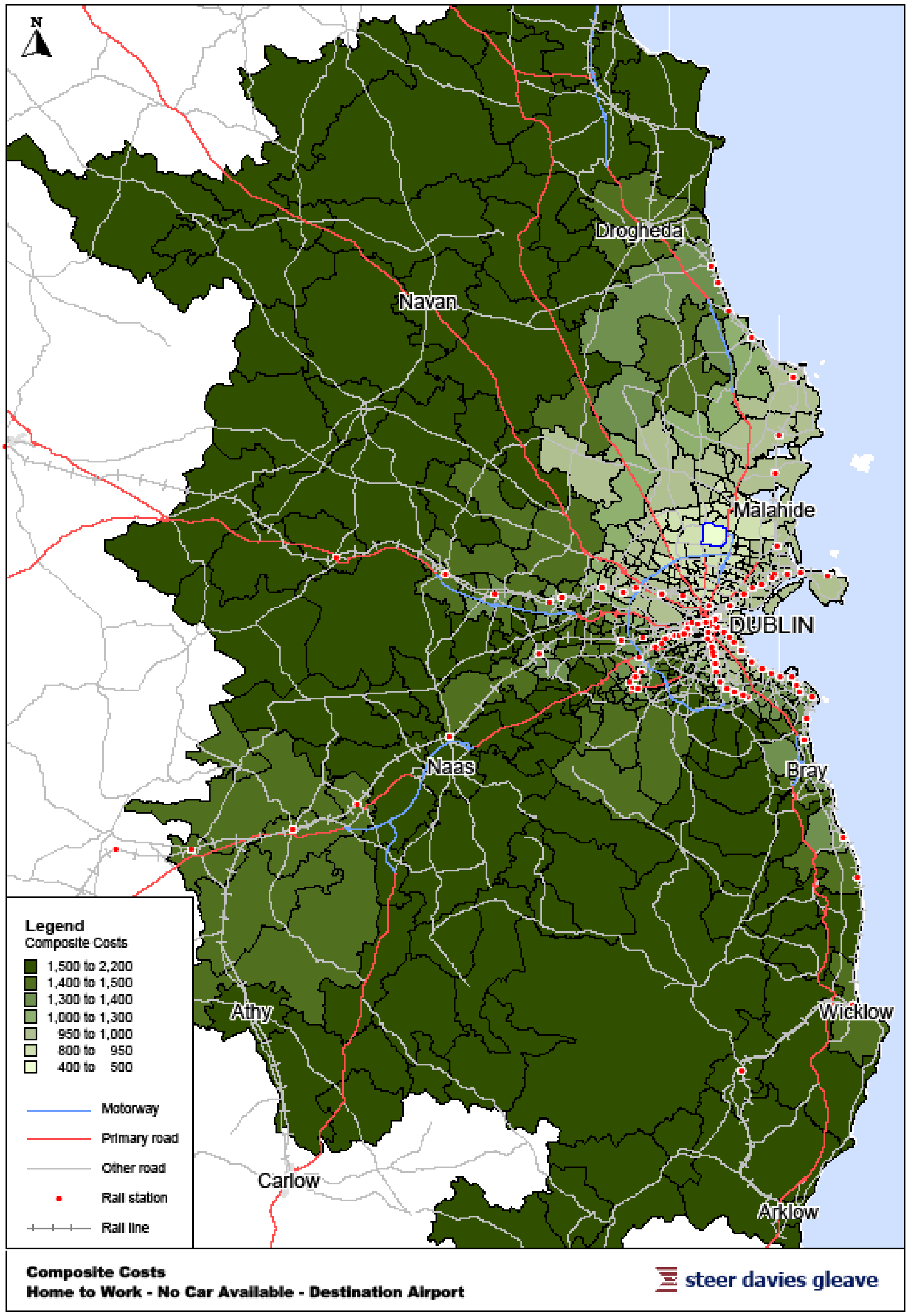


FIGURE 4.19 COMPOSITE COSTS - COMMUTE CAR NON AVAILABLE - TO AIRPORT



Summary of Calibration

Commuting Trips

4.48 The Commuting Time of Travel models achieved a reasonable level of fit, both at an aggregate and individual OD pair level. Furthermore, the implied elasticities were within the range quoted in published sources and given commuting trips (and particularly PT commuting trips) are considered non-discretionary journeys, the fact that the fuel and fare price elasticities were positioned towards the lower end of this range made initiative sense.

4.49 The mode choice calibration for commuting trips achieved a good level of fit at an aggregate level and indeed at an OD pair level for car trips. However, a poorer level of fit was noted for slow modes and particularly PT. This is attributed to the factors listed below.

4.50 **One Dominant Alternative:** Car is the dominant mode of choice accounting for 86% of all trips. With comparably lower proportions for PT and slow modes it is necessary to tolerate much larger errors between modelled and observed demand

4.51 **Cost Inputs:** In the Time of Choice calibration, the costs were split at component level (e.g. fares, in-vehicle travel time, transfers, etc). This allowed for a parameter to be estimated for each individual component which ultimately gives rise to a greater degree of model fit. In the case of the Mode Choice calibration, the cost inputs were the log-summed composite costs derived from the Time of Choice calibration. As a result, the Mode Choice calibration only estimated scaling parameters and mode constants. With fewer degrees of freedom it was harder to achieve the same goodness of fit as observed in the Time if Choice Calibration.

4.52 **Return Journeys**: There were an insufficient number of work to home journeys to allow these to be modelled separately and so for practical considerations, these were combined within the Home to Work model. In reality, work to home trips do not involve a Mode Choice as the traveller is already 'committed' to the mode used on the outward leg. The inclusion of the return journeys in the Mode Choice calibration introduces some variability into the model which would help explain some of the poor fit.

4.53 However despite these issues, the calibration has passed a number of additional realism tests; the alternative specific constants obtained in the Time of Choice and Mode Choice calibration are of the sign expected and the scaling parameters are of the magnitude expected. Furthermore, geographical analysis has found the trends in the resultant composite costs to be rational and explainable – with costs lowest in zones closest to the destination zones and highest in zones further from the destination zone. Therefore, taking all factors into account, we consider the overall calibration to be reasonable and equally important, intuitively sensible.

Remaining Journey Purposes

4.54 The full results of the Time of Travel and Mode Choice calibration process for the remaining five journey purposes; HB, HE, HS, HO, NHB are contained within Appendix B. However we provide a summary of these in the section that follows.

4.55 In general, across all journey purposes, the Goodness of Fit obtained at an aggregate level (i.e. across all OD pairs) was very good (typically less than 5%).

4.56 The Goodness of Fit at an individual OD level was unsurprisingly less good than at the overall level. This was particularly the case where there were:

- a low number of trips in an arrival time band (for Time of Choice);
- or mode (for Mode Choice – PT was particularly problematic given the relatively small proportion of PT trips – see Table 4.9); and
- or where the proportion of return trips was high (as in the case of highway Home to Education trips where there was a significant number of escort return trips – arguably these return trips do not involve a mode choice as the traveller is tied into the mode used on the outward leg of the journey).

TABLE 4.9 NUMBER OF TRIPS BY SEGMENT: MODE CHOICE

	Car Available Trips				Car Non Available Trips		
	Highway	**PT**	**Slow**	**Total**	**PT**	**Slow**	**Total**
Home to Work	86%	5%	9%	**448,339**	41%	59%	**216,713**
Home to Education	84%	5%	11%	**190,068**	32%	68%	**128,218**
Home to Shop	81%	2%	17%	**28,915**	26%	74%	**17,777**
Home to Other	82%	2%	16%	**66,106**	31%	69%	**20,320**
Home to Business	92%	3%	5%	**12,490**	46%	54%	**5,509**
Non Home Based	93%	3%	4%	**60,171**	61%	39%	**11,965**

4.57 Where results indicated a poor model fit, the calibration process was repeated in an effort to obtain parameter values which produced an improved level of fit. Throughout the process the values and signs of the parameters were checked to ensure they were sensible (e.g. negative Alternative Specific Constants on alternatives that were particularly popular relative to the other alternatives indicating their lower relative cost).

4.58 The results of the realism tests are shown in Table 4.10. Note that the following abbreviations have been used: HE for Home to Education, HB for Home to Business, HS for Home to Shop, HO for Home to Other, and NHB for Non Home Based Business.

TABLE 4.10 IMPLIED ELASTICITY VALUES

Elasticity	HE	HB	HS	HO	NHB
Fuel Price (7-8)	-0.064	-0.258	-0.283	-0.233	-0.254
Fuel Price (8-9)	-0.061	-0.252	-0.249	-0.219	-0.236
Fuel Price (9-10)	-0.041	-0.218	-0.034	-0.076	-0.150
Highway Travel Time (7-8)	-0.145	-0.089	-0.257	-0.303	-0.398
Highway Travel Time (8-9)	-0.055	-0.102	-0.251	-0.082	-0.241
Highway Travel Time (9-10)	-0.103	-0.105	-0.094	-0.112	-0.282
Fare Price (7-8)	-0.072	-0.053	-0.617	-0.599	-0.105
Fare Price (8-9)	-0.046	-0.055	-0.604	-0.588	-0.048

Elasticity	HE	HB	HS	HO	NHB
Fare Price (9-10)	-0.056	-0.055	-0.565	-0.543	-0.060
PT Travel Time (7-8)	-0.194	-0.089	-0.178	-0.673	-0.129
PT Travel Time (8-9)	-0.060	-0.068	-0.123	-0.550	-0.055
PT Travel Time (9-10)	-0.130	-0.107	-0.076	-0.679	-0.099

4.59 For Home to Education (HE) trips, the demand elasticities with respect to fuel costs are very low indicating that such travellers are quite insensitive to change in the cost of highway travel. This is sensible given that trips to school/college/university are at the most non-discretionary end of the scale. The same appears true of public transport HE and HB users. For these groups the fare price elasticities are all less than -0.01 in absolute terms. NHB PT users also display a low fare elasticity; this may be due to these travellers having already chosen their mode of transport on the outward leg of their journey and so on their NHB trip they are somewhat “locked into” using the PT mode.

4.60 Both HO and HS trips produce higher PT fare elasticises which again is sensible given that these trips are towards the more discretionary end of the scale where travellers have more of a chose as to whether to make the journey at all.

4.61 For highway trips, the demand elasticities with respect to journey time are smallest for the HE and HB journey purposes (i.e. the more non-discretionary journey purposes) and larger (or more negative) for HS and NHB journeys (indicating that for these journeys, more travellers are likely to change their travel behaviour if they experience a change in travel time.

4.62 For PT trips, the demand elasticities with respect to travel time are lowest for HB trips. This is sensible as there is likely to be less sensitivity to increases in travel time for these types of trips (passengers travelling on business may be tied into arriving at their destination for a particular meeting and so have less scope to travel later or not at all. Furthermore, they may be reluctant to switch to car travel during the AM peak period).

4.63 In general the implied elasticities generated by the calibration process are broadly in line with published sources (Webtag: typical elasticity ranges – Fuel -0.1 to -0.4, Fare -0.2 to -0.4 but up to -0.9 for changes over longer periods, travel time – less than -2.0 in absolute terms) and the variation by journey purpose is intuitively sensible.

5. RECOMMENDATIONS

Conclusions

5.1 This report has described the calibration of the Time of Travel Choice and Mode Choice stages of the DTO AM Peak model across six journey purposes. Each stage of the process has been described from initially receiving the input data through to testing the output and producing the main deliverables which were sets of parameter estimates for use within the DTO model.

5.2 Through rigorous data analysis, we were able to optimise the quality of the input data thus maximising the likelihood of finding parameter estimates that would satisfy our strict success criteria. These criteria not only looked to address requirements in model fit but also adherence to regulatory best practice guidelines (i.e. ensuring implied elasticities were within the ranges quoted by Webtag – the guidance provided by the UK DfT).

5.3 The calibration process entailed the use of a Multi-Objective Market Simulation Tool and by systematically running the tool, interpreting the results and making incremental modifications; we were able to obtain finalised sets of estimated parameter values that were both realistic and provided reasonable levels of model fit.

5.4 The geo-analysis carried out on the output composite costs provided further evidence that the process had resulted in a calibration that was fit for purpose and intuitively sensible.

5.5 At SDG we are relentless in an endeavour to continuously improve and throughout this project we have noted certain opportunities to further enhance this process in the future and we have documented these below.

Recommendations for Future Enhancements

5.6 **Simultaneous recalibration:** This project required two sets of consultancies to work on different stages of the model at the same time. Whilst we recognise that the interaction and communication between Minnerva and ourselves was generally effective and efficient it did not allow for the simultaneous recalibration of several stages of the model at the same time and we would propose that in the future, the calibration of all five stages undertaken solely by a single consultant would be a worthy consideration.

5.7 **Return Journeys:** Throughout the Time of Travel Choice and Mode Choice calibration, return journeys, being too small in number to model separately, were combined with their outward leg. Whilst from a pragmatic viewpoint this was a suitable approach to take, there was some evidence to suggest that this led to a slight deterioration in model fit at the OD level (this was most notable in Home to Education highway trips where there was a higher proportion of return journey escort trips during the AM peak). To overcome this in the future, the DTO may wish to consider the use of "tours" rather than "trips". By doing so return legs could be linked to their outward legs and modelled separately. In other words for modelling Time of Travel Choice: of the trips travelling out between 7-8, x% return in the hour, y% return in 8-9 hour and z% return in the 9-10 hour. And for modelling Mode Choice return mode=outward mode. This would appear sensible given that return journeys generally do not involve a choice about mode as the traveller is tied in to the mode used for the outward leg of the journey.

5.8 **Introduction of additional skims:** The skims used within the process may have helped to describe much of the perceived costs of travel faced by the traveller; however, the list of skims was not exhaustive. The DTO may wish to consider adding further skims, particularly on soft measures (e.g. comfort of journey) to better capture these perceived costs.

5.9 **Park and Ride:** The Mode Choice Calibration was concerned with three modes; Highway, Public Transport and Slow Modes. It is understood that the DTO's CUBE/TRIPS interface also included Park and Ride as a separate mode within the Highway nest and in order to retain consistency and rigour the DTO may wish to consider Park and Ride as in-scope for the Mode Choice calibration exercise in the future.

5.10 **Reliability of Public Transport:** The current model does not take account of the reliability of PT and how much a risk of delay to journey features in a passenger's decision around mode choice. This may be another area the DTO wish to explore in the future.

5.11 **Obtaining more data:** Throughout the calibration process it was evident that for some journey purpose mode segments the amount of data was relatively small and this in turn led to results with greater inherent variability. To improve on this in the future, the DTO may wish to consider undertaking further analysis to identify the segments with very small proportions of total trips (generally, the smallest segments are the public transport car available segments, as indicated by Table 4.9, where the proportion of total trips is just 2% to 3%) and capture more data in these areas to improve future model fit.

APPENDIX A

DETAILED CALIBRATION RESULTS

A1. SUMMARY OF RESULTS

Estimated Parameter Values

A1.1 This section provides parameter values for each model estimated.

Highway Time of Travel Results

APPENDIX: TABLE A1.1 Highway Time of Travel Choice

Parameter Code	Parameter	Commute (HW)	Home to Education (HE)	Home to Shop (HS)	Home to Other (HO)	Home to Business (HB)	Non-Home Based (NHBO)
HWAY1	Distance (7-8)	1.180	0.580	2.530	1.060	5.456	1.486
HWAY2	Distance (8-9)	2.150	1.512	2.167	7.232	6.134	2.446
HWAY3	Distance (9-10)	3.425	0.643	1.142	1.276	4.801	1.851
HWAY4	Time (7-8)	1.000	1.000	1.000	1.000	1.000	1.000
HWAY5	Time (8-9)	1.000	1.000	1.000	1.000	1.000	1.000
HWAY6	Time (9-10)	1.000	1.000	1.000	1.000	1.000	1.000
HWAY7	Toll (7-8) calibration parameter	1.232	3.031	1.225	2.479	0.421	2.802
HWAY8	Toll (8-9) calibration parameter	2.409	2.459	2.231	2.321	0.250	1.852
HWAY9	Toll (9-10) calibration parameter	0.863	2.712	2.199	2.193	0.380	1.667
HWAY10	Constant (8-9)	-50.246	-308.538	-20.152	-51.326	-56.605	-76.319
HWAY11	Constant (7-9)	-55.830	262.479	97.628	76.963	32.513	94.111
HWAY12	Scaling Parameter	0.005	0.011	0.023	0.016	0.006	0.023
HWAY13	7-9 Scaler	0.013	0.011	0.023	0.024	0.006	0.023

Public Transport Time of Travel Results

APPENDIX: TABLE A1.2 Public Transport Time of Travel Choice

Parameter Code	Parameter	Commute (HW)	Home to Education (HE)	Home to Shop (HS)	Home to Other (HO)	Home to Business (HB)	Non-Home Based (NHBO)
PT1	Walk (7-8)	1.203	5.593	4.876	4.453	4.394	7.747
PT2	Walk (8-9)	0.856	6.290	2.884	4.781	4.550	4.591
PT3	Walk (9-10)	2.026	4.880	3.892	3.929	4.621	4.876
PT4	IVT (7-8)	1.000	1.000	1.000	1.000	1.000	1.000
PT5	IVT (8-9)	1.000	1.000	1.000	1.000	1.000	1.000
PT6	IVT (9-10)	1.000	1.000	1.000	1.000	1.000	1.000
PT7	Wait (7-8)	8.763	8.729	4.536	3.894	4.848	5.147
PT8	Wait (8-9)	3.678	7.497	1.026	7.561	4.964	7.634
PT9	Wait (9-10)	0.174	7.518	2.533	6.528	4.761	3.492
PT10	Transfer (7-8)	0.274	10.257	6.453	3.733	5.296	9.299
PT11	Transfer (8-9)	6.621	10.992	6.490	5.287	6.371	0.261
PT12	Transfer (9-10)	9.400	9.519	2.058	4.792	4.758	3.883
PT13	Fare (7-8) calibration parameter	3.638	3.985	0.413	1.494	0.676	1.523
PT14	Fare (8-9) calibration parameter	2.069	2.153	0.322	1.513	0.541	1.480
PT15	Fare (9-10) calibration parameter	3.424	3.783	0.195	1.734	0.841	2.119
PT16	Constant (8-9)	-23.656	-139.701	-10.525	-150.482	-138.558	-110.372
PT17	Constant (7-9)	-72.264	25.170	118.942	116.534	-103.017	77.657
PT18	Scaling Parameter	0.010	0.015	0.012	0.317	0.004	0.007

APPENDIX: TABLE A1.3 Car Available Mode Choice

Parameter Code	Parameter	Commute (HW)	Home to Education (HE)	Home to Shop (HS)	Home to Other (HO)	Home to Business (HB)	Non-Home Based (NHBO)
CA1	PT Mode Constant	200.000	50.000	200.000	91.220	249.881	150.000
CA2	Mechanised Mode Constant	-107.761	-120.333	-149.289	-83.108	-29.838	-150.000
CA3	Scaling Parameter	0.00652	0.01000	0.01100	0.01400	0.01600	0.01664
CA4	Mechanised Mode Scaling Parameter	0.00733	0.01100	0.01100	0.01408	0.01600	0.01699

APPENDIX: TABLE A1.4 Car Non-Available Mode Choice

Parameter Code	Parameter	Commute (HW)	Home to Education (HE)	Home to Shop (HS)	Home to Other (HO)	Home to Business (HB)	Non-Home Based (NHBO)
CNA1	PT Mode Constant	200.000	50.000	-36.069	-46.284	374.355	-143.618
CNA2	Scaling Parameter	0.00388	0.00672	0.02309	0.01101	0.00417	0.00261

Generalised Cost Calculations – Time of Travel

PT

Equation Code		
EQ1	Generalised Cost (7-8)	= pt_7-8_walk*[PT1] + pt_7-8_ivt*[PT4] + pt_7-8_wait*[PT7] + pt_7-8_xfer*[PT10] + (pt_7-8_fare/([PT13]*VoT)) + pt_7_crowd*[PT20]
EQ2	Generalised Cost (8-9)	= pt_8_walk*[PT2] + pt_8_ivt*[PT5] + pt_8_wait*[PT8] + pt_8_xfer*[PT11] + (pt_8_fare/([PT14]*VoT)) + pt_8_crowd*[PT21] + [PT16]
EQ3	Generalised Cost (9-10)	= pt_9_walk*[PT3] + pt_9_ivt*[PT6] + pt_9_wait*[PT9] + pt_9_xfer*[PT12] + (pt_9_fare/([PT15]*VoT)) +pt_9_crowd*[PT22]
EQ4	Generalised Cost (7-9)	= (-1/[PT19])*ln(exp(-[EQ1]*[PT19]) + exp(-[EQ2]*[PT19]))
EQ5	Generalised Cost (7-9) v	= [EQ4]+[PT17]
EQ6	Probability (7-9)	= exp(-[EQ5]*[PT18])/(exp(-[EQ5]*[PT18])+exp(-[EQ3]*[PT18]))
EQ7	Probability (9-10)	= exp(-[EQ3]*[PT18])/(exp(-[EQ5]*[PT18])+exp(-[EQ3]*[PT18]))
EQ8	Probability (7-8)	= [EQ6] * (exp(-[EQ1]*[PT19])/(exp(-[EQ1]*[PT19])+exp(-[EQ2]*[PT19])))
EQ9	Probability (8-9)	= [EQ6] * (exp(-[EQ2]*[PT19])/(exp(-[EQ1]*[PT19])+exp(-[EQ2]*[PT19])))

VoT Values (sourced from the 2004 GEC report, in 2006 prices)

Non Business Trips – 9.476 euros/hr

Business Trips– 31.00 euros/hr

Highway

Equation Code		
EQ10	Generalised Cost (7-8)	=hw_7_dist*[HWAY1] + hw_7_time*[HWAY4] + (hw_7_toll/([HWAY7]*VoT))
EQ11	Generalised Cost (8-9)	=hw_8_dist*[HWAY2] + hw_8_time*[HWAY5] + (hw_8_toll/([HWAY8]*VoT)) + [HWAY10]
EQ12	Generalised Cost (9-10)	=hw_9_dist*[HWAY3] + hw_9_time*[HWAY6] + (hw_9_toll/([HWAY9]*VoT))
EQ13	Generalised Cost (7-9)	= (-1/[HWAY13])*ln(exp(-[EQ10]*[HWAY13]) + exp(-[EQ11]*[HWAY13]))
EQ14	Generalised Cost (7-9) v	=[EQ13] + [HWAY11]
EQ15	Probability (7-9)	=exp(-[EQ14]*[HWAY12])/(exp(-[EQ14]*[HWAY12])+exp(-[EQ12]*[HWAY12]))
EQ16	Probability (9-10)	=exp(-[EQ12]*[HWAY12])/(exp(-[EQ14]*[HWAY12])+exp(-[EQ12]*[HWAY12]))
EQ17	Probability (7-8)	= [EQ15] * (exp(-[EQ10]*[HWAY13])/(exp(-[EQ10]*[HWAY13])+exp(-[EQ11]*[HWAY13])))
EQ18	Probability (8-9)	= [EQ15] * (exp(-[EQ11]*[HWAY13])/(exp(-[EQ10]*[HWAY13])+exp(-[EQ11]*[HWAY13])))

Composite Cost Inputs for Mode Choice

Prior to Mode Choice Calibration, the generalised costs for each of the three hour bands were combined using a log-sum formulation:

<u>Equation Code</u>

EQ19 Generalised Cost PT (7-10) = ((-1/**[PT18]**)*ln(exp(-**[EQ5]***[PT18]**) + exp(-**[EQ3]***[PT18]**)))
EQ20 Generalised Cost Highway (7-10) = ((-1/**[HWAY12]**)*ln(exp(-**[EQ14]***[HWAY12]**) + exp(-**[EQ12]***[HWAY12]**)))

At this stage we also introduce slow modes, we estimate costs for slow modes as follows:

Assuming Cycle speed = 15 kph, walk speed = 5kph

Separately for each journey purpose, we use the highway distance for each OD pair from the 8 to 9 hourband to calculate a weighted average SM travel time

The average is weighted depending on distance. See table below for weights

Data Source: the proportions were obtained from analysis of the initial SM trip matrices

APPENDIX: TABLE A1.5 Split of SM trips by walkers/cyclists (For Commute, HB, and HE journey purposes)

Distance (km)	Proportion of SM trips which are walkers	Proportion of SM trips which are cyclists
0-2	0.85	0.15
2-4	0.73	0.27
4-6	0.61	0.39
6-8	0.59	0.41
8-10*	0.38	0.62
10-12*	0.19	0.81
+12*	0	1

*These were inter-polated as data was unreliable for these distances

APPENDIX: TABLE A1.6 Split of SM trips by walkers/cyclists (HO)

Distance (km)	Proportion of SM trips which are walkers	Proportion of SM trips which are cyclists
0-2	0.93	0.07
2-4	0.92	0.08
4-6	0.9	0.1
6-8	0.5	0.5
8-10*	0.38	0.62
10-12*	0.19	0.81
+12*	0	1

*These were interpolated as data was unreliable for these distances

APPENDIX: TABLE A1.7 Split of SM trips by walkers/cyclists (HS)

Distance (km)	Proportion of SM trips which are walkers	Proportion of SM trips which are cyclists
0-2	0.86	0.14
2-4	0.86	0.14
4-6	0.86	0.14
6-8	0.67	0.33
8-10*	0.38	0.62
10-12*	0.19	0.81
+12*	0	1

*These were interpolated as data was unreliable for these distances

APPENDIX: TABLE A1.8 Split of SM trips by walkers/cyclists (NHB)

Distance (km)	Proportion of SM trips which are walkers	Proportion of SM trips which are cyclists
0-2	0.83	0.17
2-4	0.83	0.17
4-6	0.83	0.17
6-8	0.67	0.33
8-10*	0.38	0.62
10-12*	0.19	0.81
+12*	0	1

*These were interpolated as data was unreliable for these distances

An example of the SM weighted average calculation is shown below:

For Commuting trips, for an OD pair where the highway distance is 1.5km =((1.5/15)*60)*0.15+((1.5/5)*60)*0.85 = 16.2 minutes

Note: Where the commuted SM travel time exceeded 75 minutes, the generalised cost was recoded to 99999 to indicate a very high cost to SM travellers

With the composite costs for Highway, PT and SM, the following Mode Choice calculations are used:

Generalised Cost Calculations – Mode Choice Car Available

Equation Code		
EQ21	Generalised Cost PT with constant	= **[EQ19]** + **[CA1]**
EQ22	Generalised Costs Mechanised Modes	= ((-1/**[CA4]**)*ln(exp(-**[EQ20]***[CA4]**) + exp(-**[EQ21]***[CA4]**)))
EQ23	Generalised Costs Mechanised Modes with constant	= **[EQ22]** + **[CA2]**
EQ24	Probability Mechanised Modes	=(exp(-**[EQ23]***[CA3]**)/(exp(-**[EQ23]***[CA3]**)+exp(-*[generalised cost of Slow Modes]* *[CA3]**)))
EQ25	Probability Slow Modes	=(exp(-*[generalised cost of Slow Modes]* *[CA3]**)/(exp(-**[EQ23]***[CA3]**)+exp(-*[generalised cost of Slow Modes]* *[CA3]**)))
EQ26	Probability Highway	=**[EQ24]** * (exp(-**[EQ20]***[CA4]**)/(exp(-**[EQ20]***[CA4]**)+exp(-**[EQ21]***[CA4]**)))
EQ27	Probability PT	=**[EQ24]** * (exp(-**[EQ21]***[CA4]**)/(exp(-**[EQ20]***[CA4]**)+exp(-**[EQ21]***[CA4]**)))

Generalised Cost Calculations – Mode Choice Car Non-Available

EQ28	Generalised Cost PT with constant	= **[EQ19]** + **[CNA1]**
EQ29	Probability Slow Modes	=(exp(-*[generalised cost of Slow Modes]* *[CNA2]**)/(exp(-**[EQ28]***[CNA2]**)+exp(-*[generalised cost of Slow Modes]* *[CNA2]**)))
EQ30	Probability PT	=(exp(-**[EQ28]***[CNA2]**)/(exp(-**[EQ28]***[CNA2]**)+exp(-*[generalised cost of Slow Modes]* *[CNA2]**)))

Resultant Composite Costs

EQ31	Car Available	= (-1/**[CA3]**)*ln(exp(-**[EQ23]***[**CA3]**)+exp(-*[generalised cost of Slow Modes]* ***[CA3]**))
EQ32	Car Not Available	= (-1/**[CNA2]**)*ln(exp(-**[EQ28]***[**CNA2]**)+exp(-*[generalised cost of Slow Modes]* ***[CNA2]**))

Analysis of the resultant composite costs indicated a significant proportion of negative costs. This is not cause for concern. The logsumming process tends to make costs smaller and negative. Applying a constant to all composite costs is permissable if the resultant composite costs are to be used in a logit function (as adding a constant does not change the relativities in the exponents)

In light of this, a constant of 1000 was applied to all costs in order to convert them all into positive numbers.

The final stage involved obtaining costs for intra-zonal journeys. During the network phase, Skims were not obtained for intra-zonal journeys and so these costs were estimated upon completion of the mode choice calibration. For each origin zone, the minimum cost to all other zones was obtained. The intra-zonal cost for each zone was then estimated to be 50% of this minimum cost value.

Appendix A

APPENDIX B

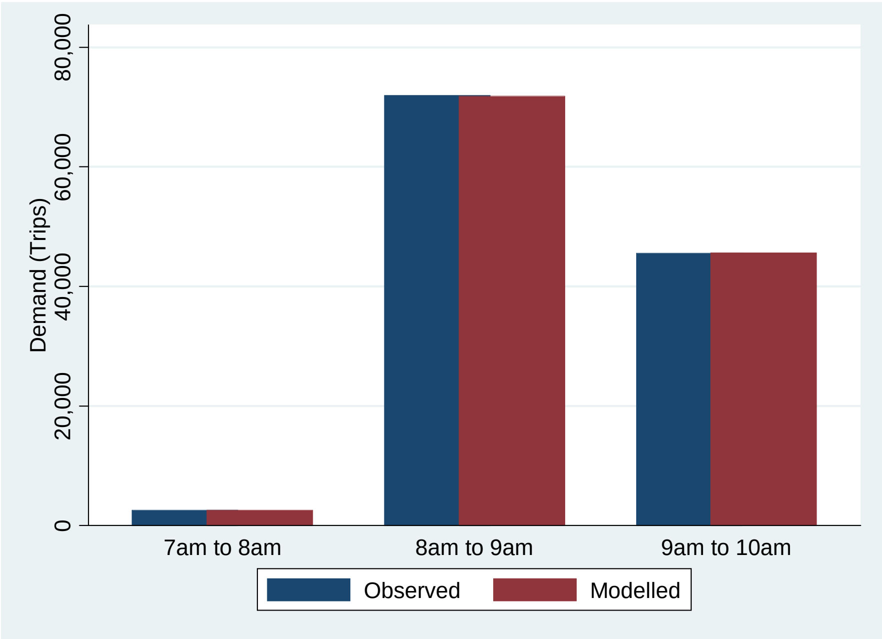
GOODNESS-OF-FIT TESTS FOR NON-COMMUTING TRIPS

B1. HOME TO EDUCATION

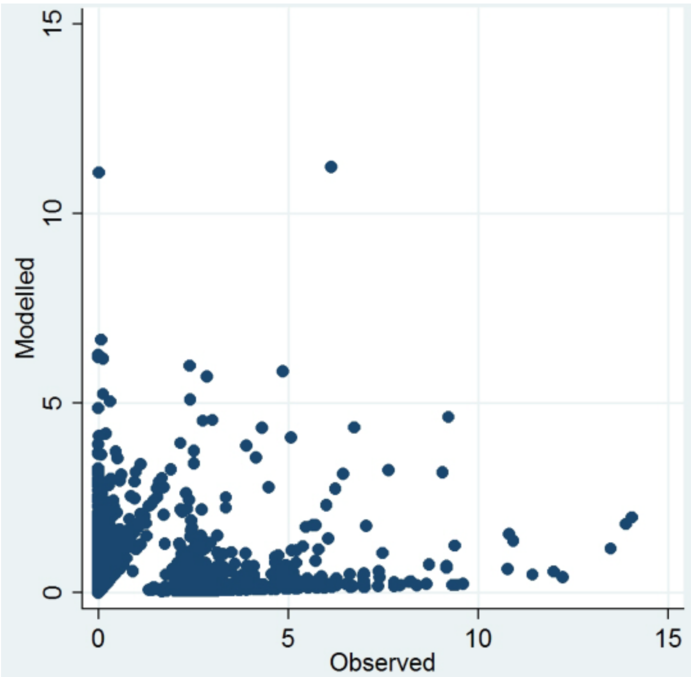
Time of Travel Choice

Highway Trips

APPENDIX: FIGURE B1.1 HOME TO EDUCATION HIGHWAY TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME

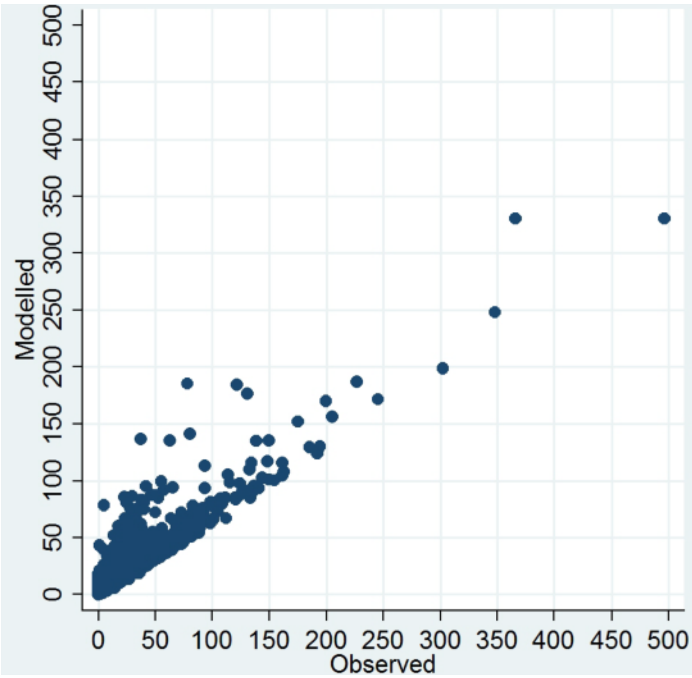


APPENDIX: FIGURE B1.2 HOME TO EDUCATION HIGHWAY DEMAND (7AM - 8AM): MODELLED V OBSERVED BY OD PAIR



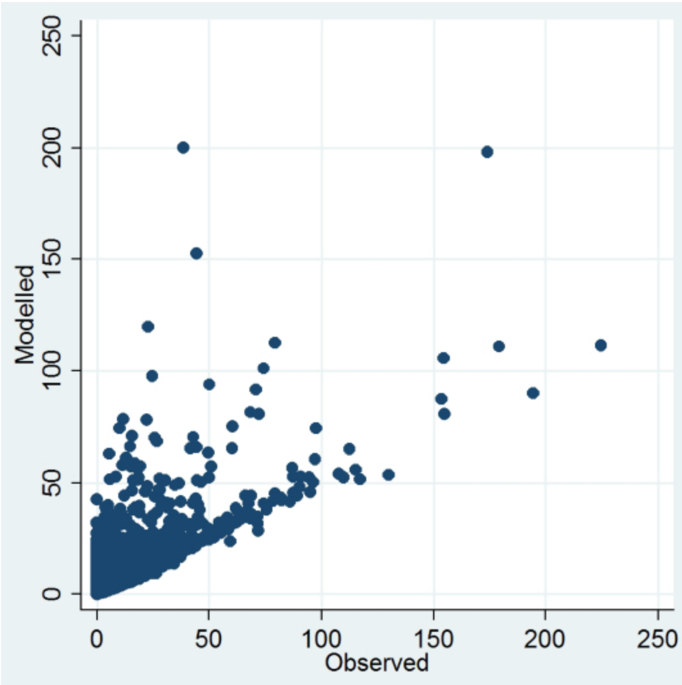
RMSWE = 3.246

APPENDIX: FIGURE B1.3 HOME TO EDUCATION HIGHWAY DEMAND (8AM - 9AM): MODELLED V OBSERVED BY OD PAIR



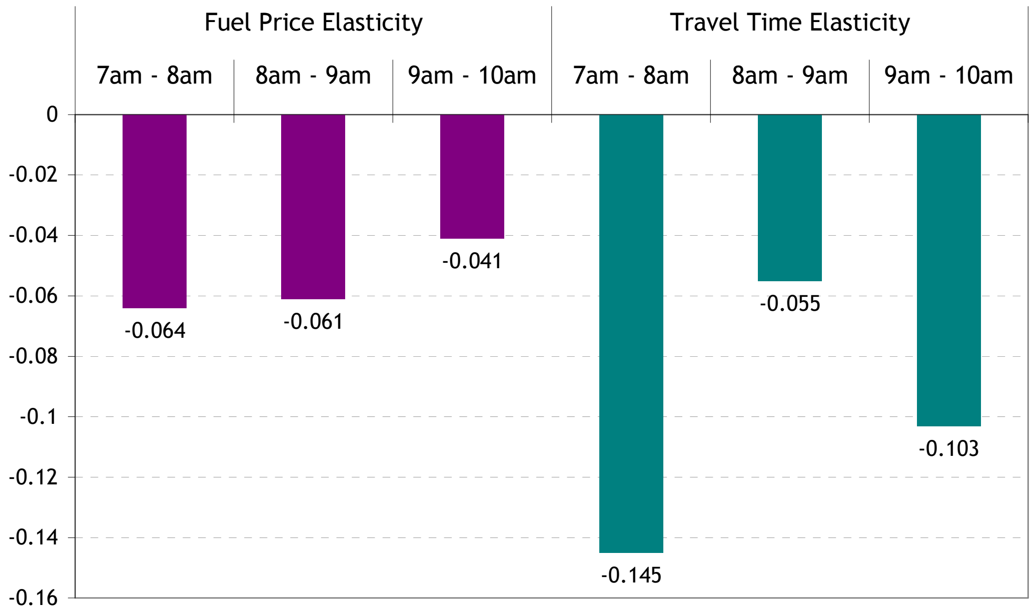
RMSWE = 0.968

APPENDIX: FIGURE B1.4 HOME TO EDUCATION HIGHWAY DEMAND (9AM - 10AM): MODELLED V OBSERVED BY OD PAIR



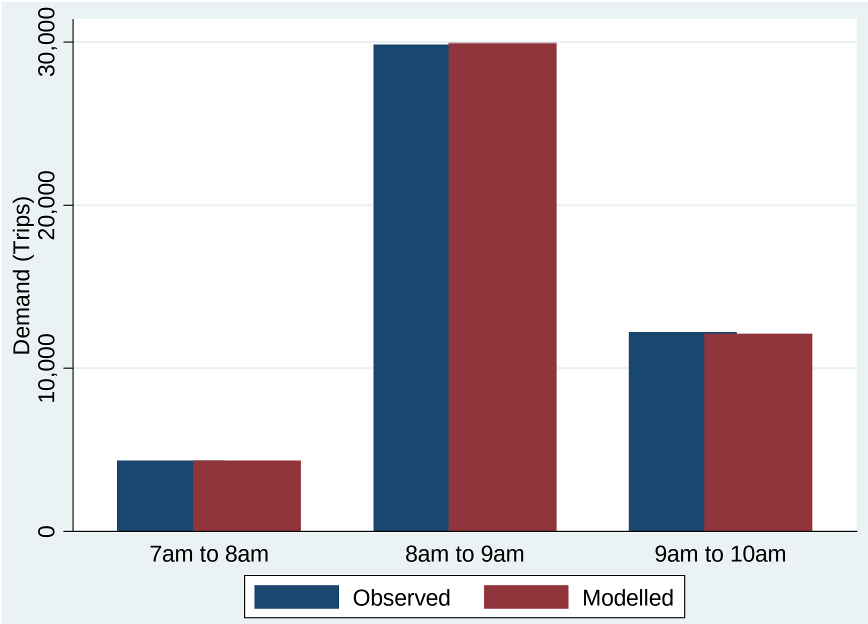
RMSWE = 4.837

APPENDIX: FIGURE B1.5 HOME TO EDUCATION HIGHWAY IMPLIED ELASTICITY VALUES

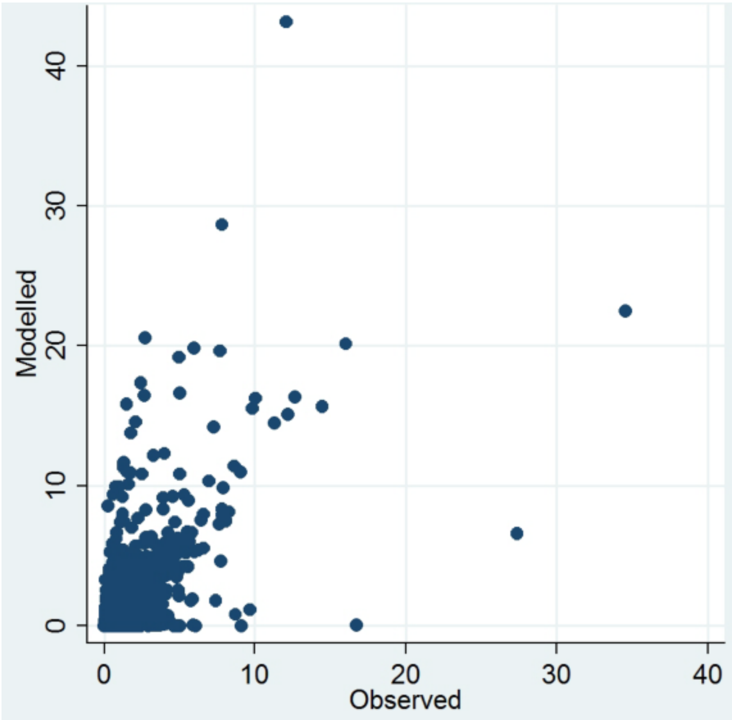


PT Trips

APPENDIX: FIGURE B1.6 HOME TO EDUCATION PT TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME

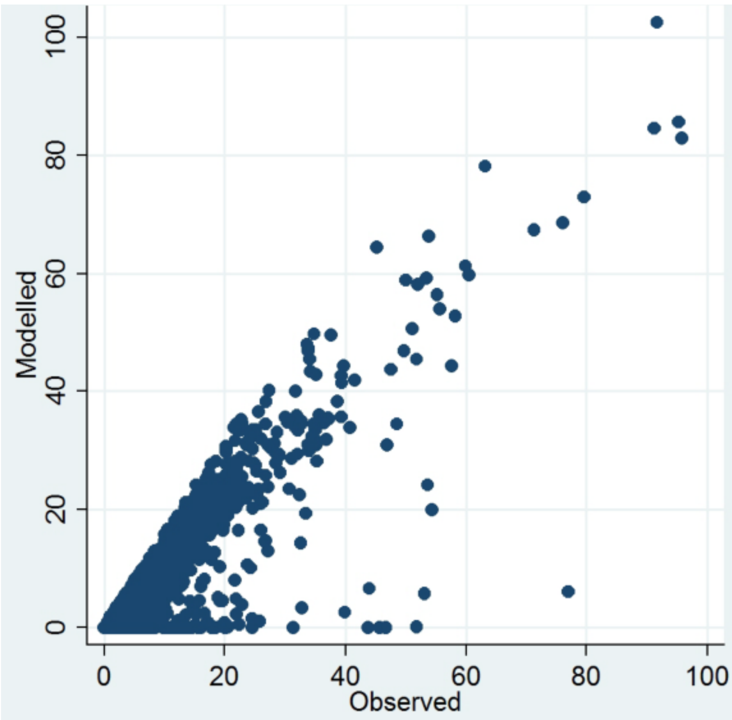


APPENDIX: FIGURE B1.7 **HOME TO EDUCATION PT TRIPS (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR**



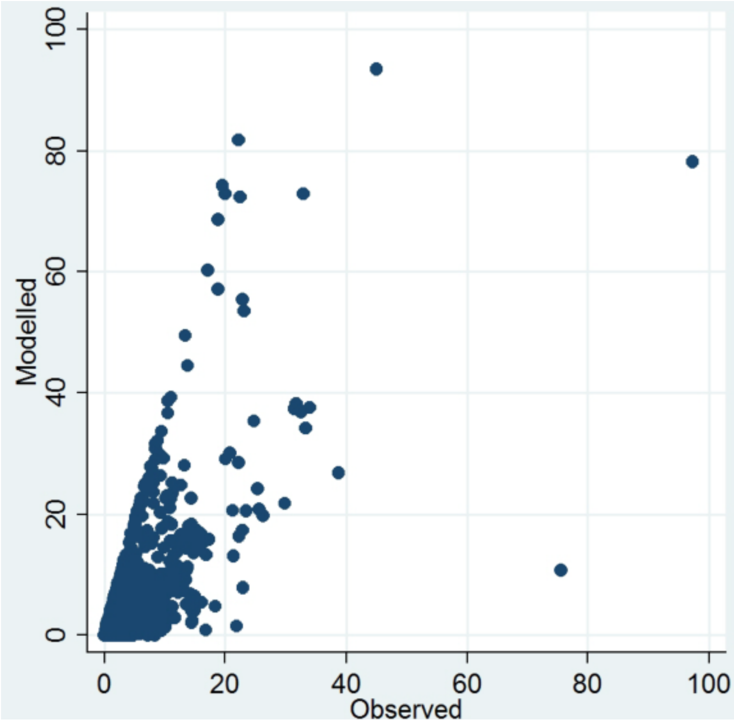
RMSWE = 1.113

APPENDIX: FIGURE B1.8 **HOME TO EDUCATION PT TRIPS (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR**



RMSWE = 0.368

APPENDIX: FIGURE B1.9 HOME TO EDUCATION PT TRIPS (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR



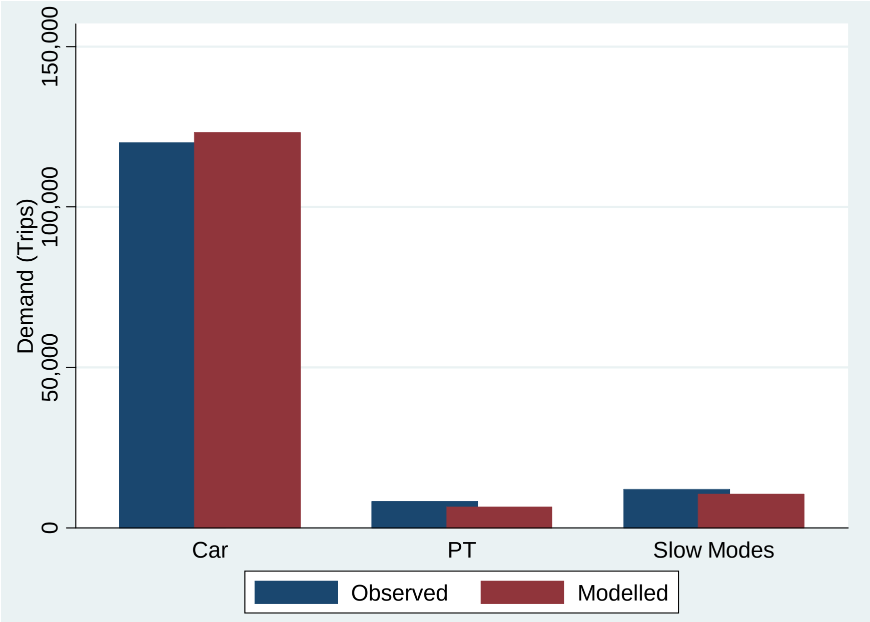
RMSWE = 0.838

APPENDIX: FIGURE B1.10 HOME TO EDUCATION PT IMPLIED ELASTICITY VALUES

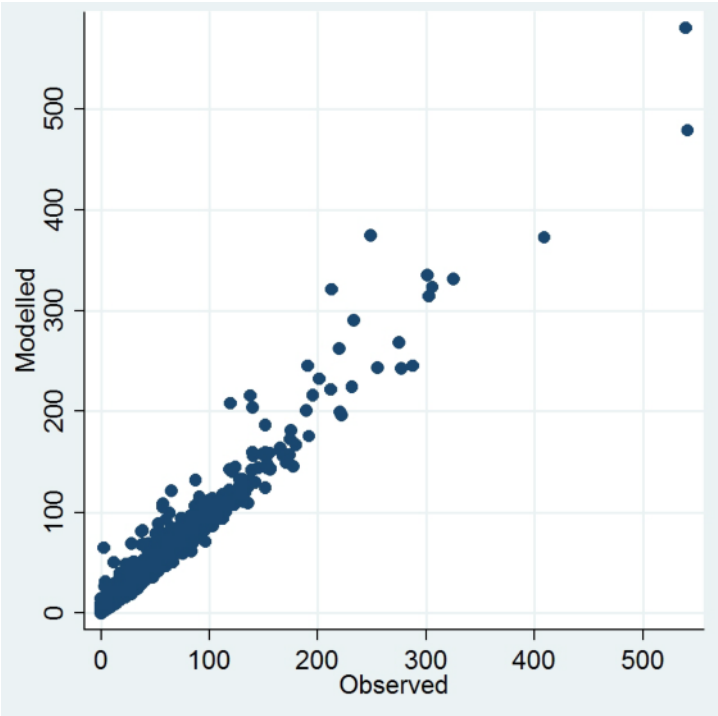
Mode Choice

Car Available

APPENDIX: FIGURE B1.11 HOME TO EDUCATION CAR AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE

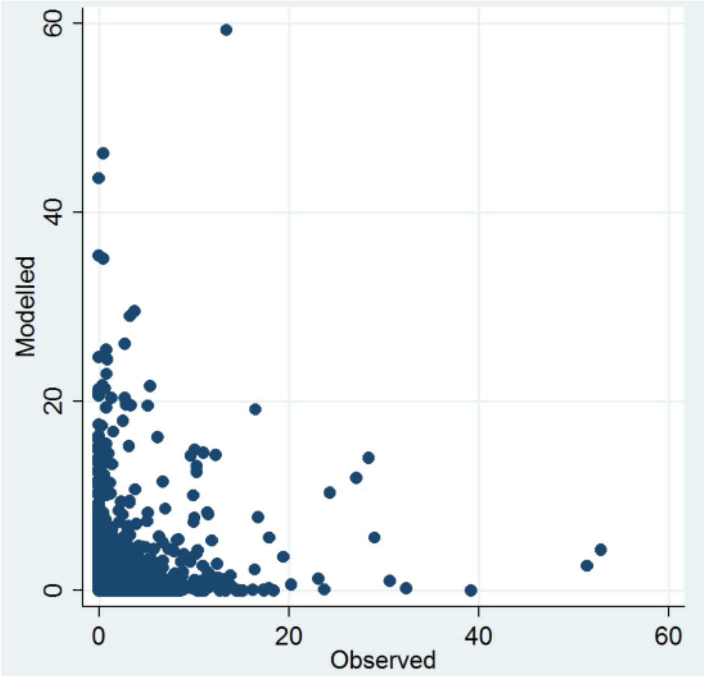


APPENDIX: FIGURE B1.12 HOME TO EDUCATION CAR AVAILABLE HIGHWAY DEMAND: MODELLED V OBSERVED BY OD PAIR



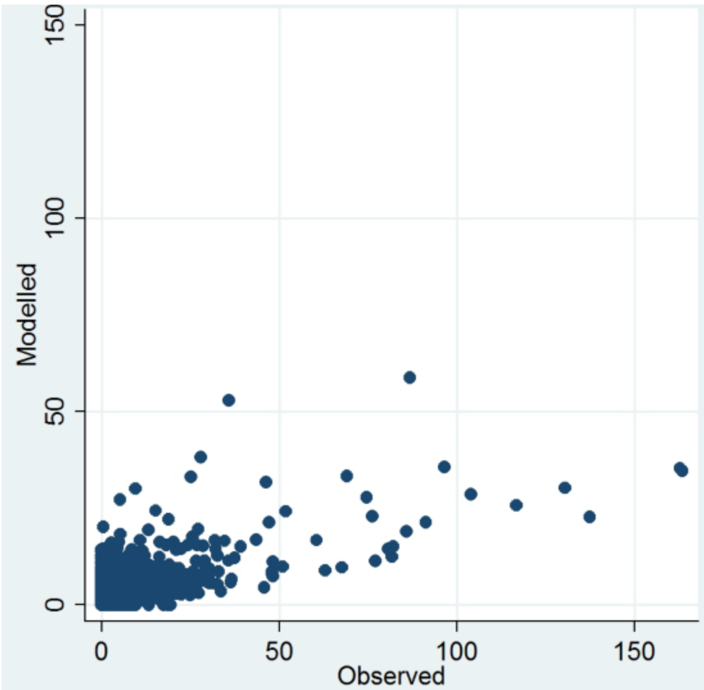
RMSWE = 1.337

APPENDIX: FIGURE B1.13 **HOME TO EDUCATION CAR AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR**



RMSWE = 150.645

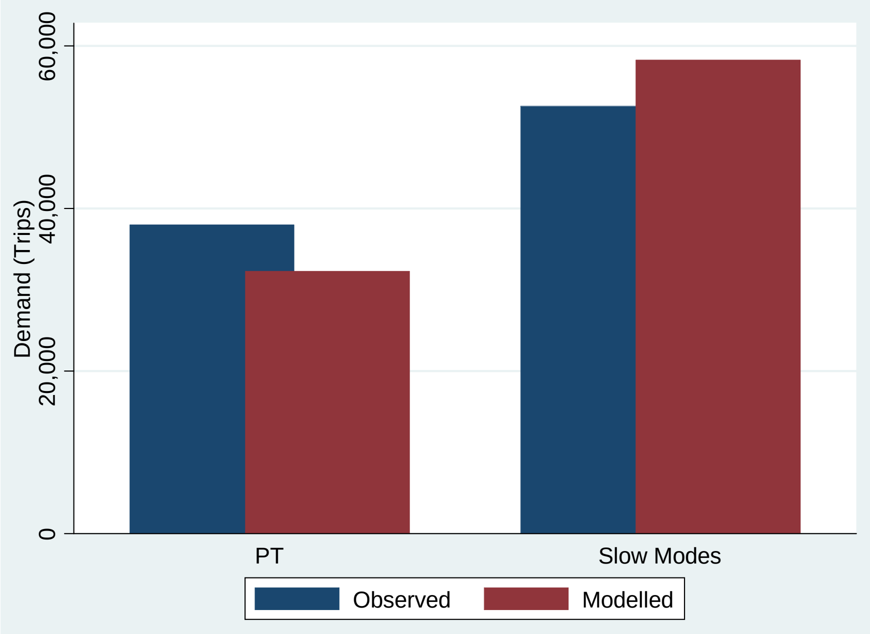
APPENDIX: FIGURE B1.14 **HOME TO EDUCATION CAR AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR**



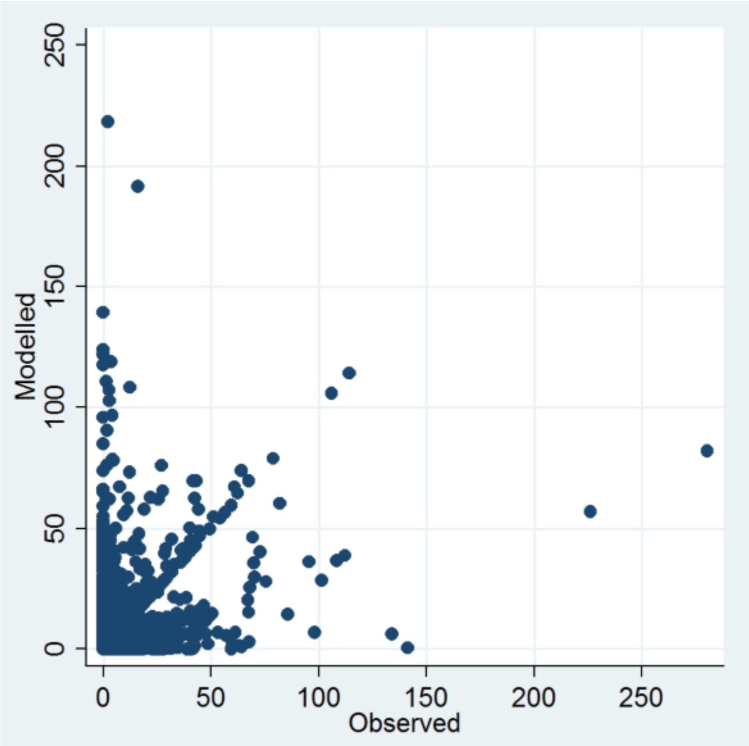
RMSWE = 5.531

Car Non-Available

APPENDIX: FIGURE B1.15 HOME TO EDUCATION CAR NON-AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE

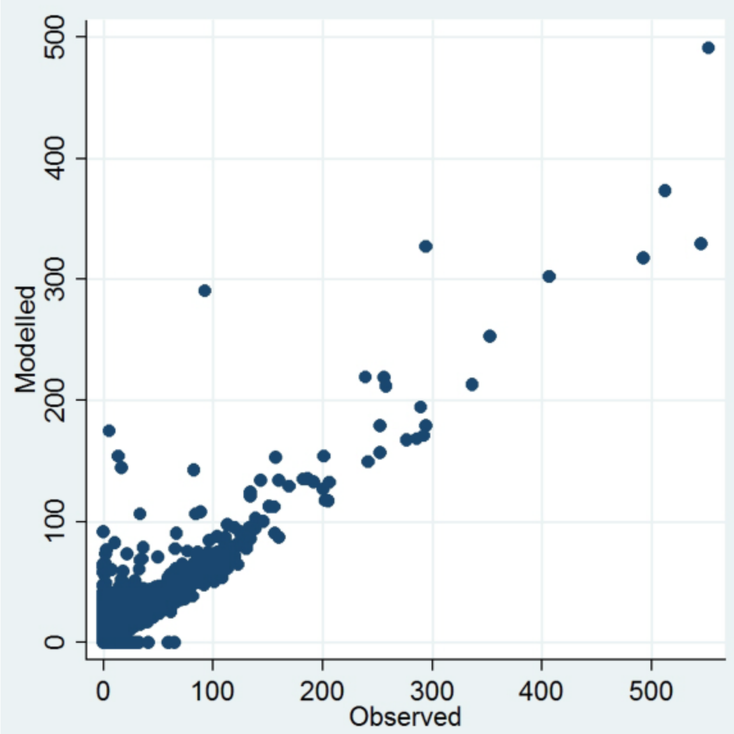


APPENDIX: FIGURE B1.16 HOME TO EDUCATION CAR NON-AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR



RMSWE =104.499

APPENDIX: FIGURE B1.17 HOME TO EDUCATION CAR NON-AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR



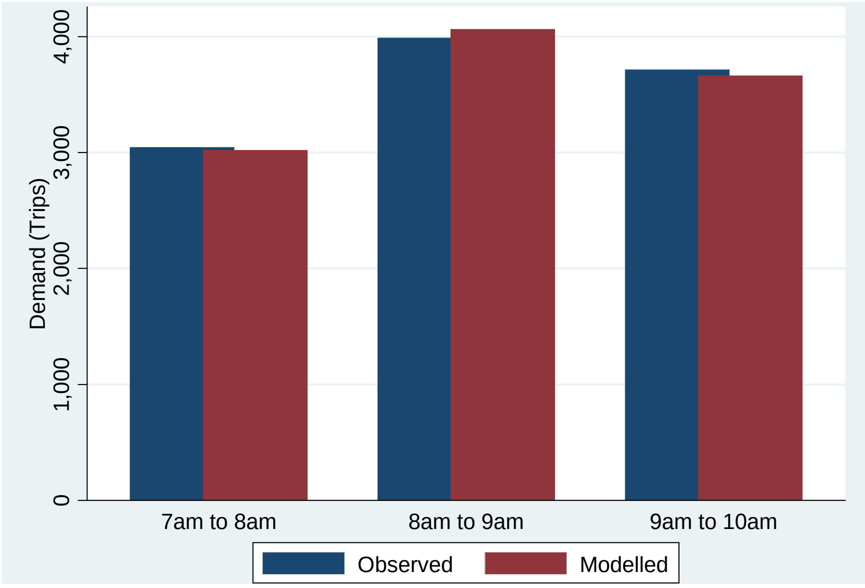
RMSWE =4.973

B2. HOME TO BUSINESS

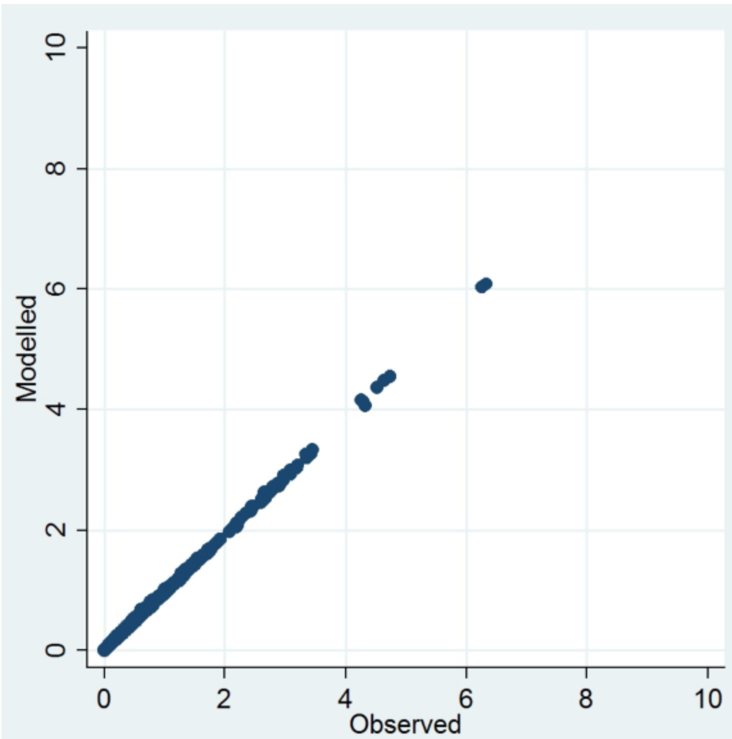
Time of Travel Choice

Highway Trips

APPENDIX: FIGURE B2.1 HOME TO BUSINESS HIGHWAY DEMAND: MODELLED V OBSERVED BY ARRIVAL TIME

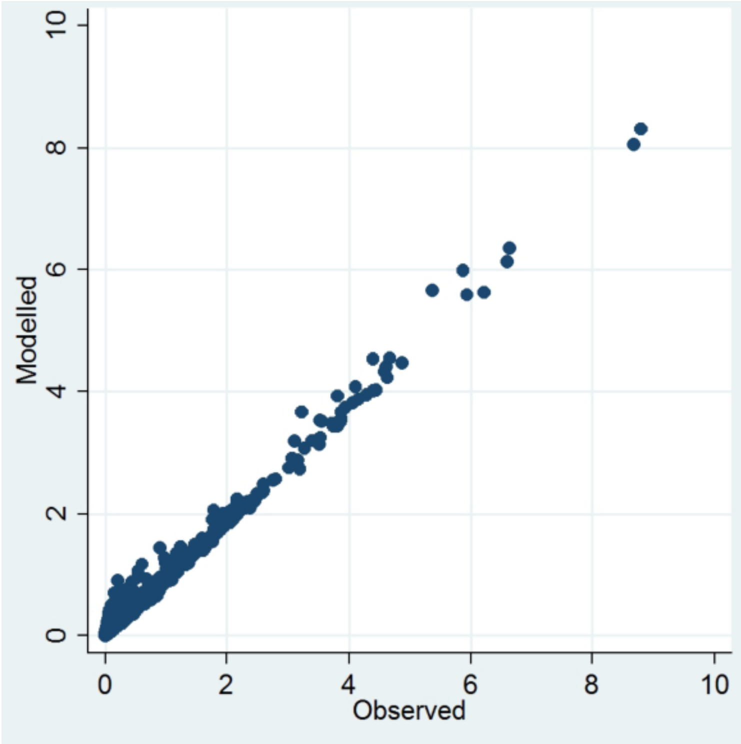


APPENDIX: FIGURE B2.2 HOME TO BUSINESS HIGHWAY DEMAND (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR



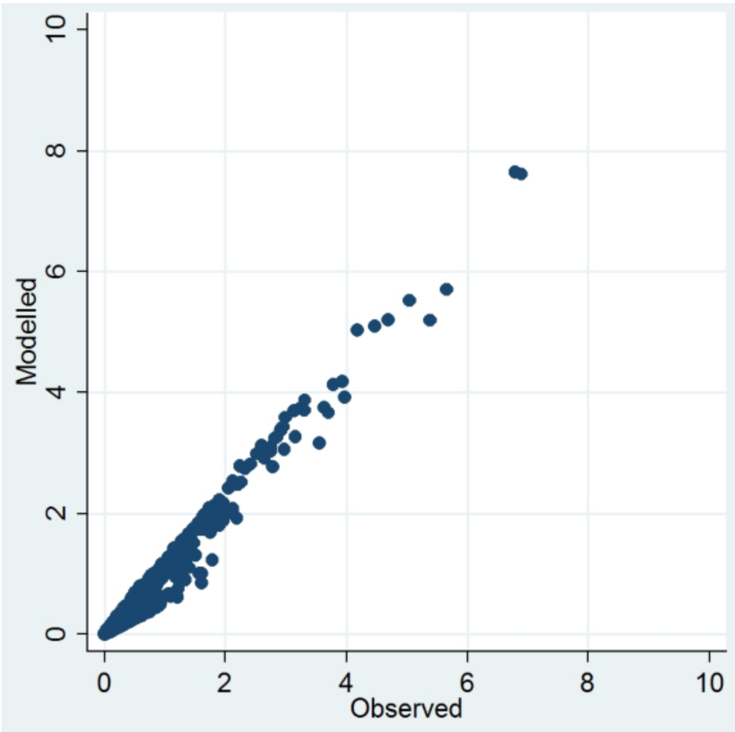
RMSWE =0.071

APPENDIX: FIGURE B2.3 **HOME TO BUSINESS HIGHWAY DEMAND (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR**



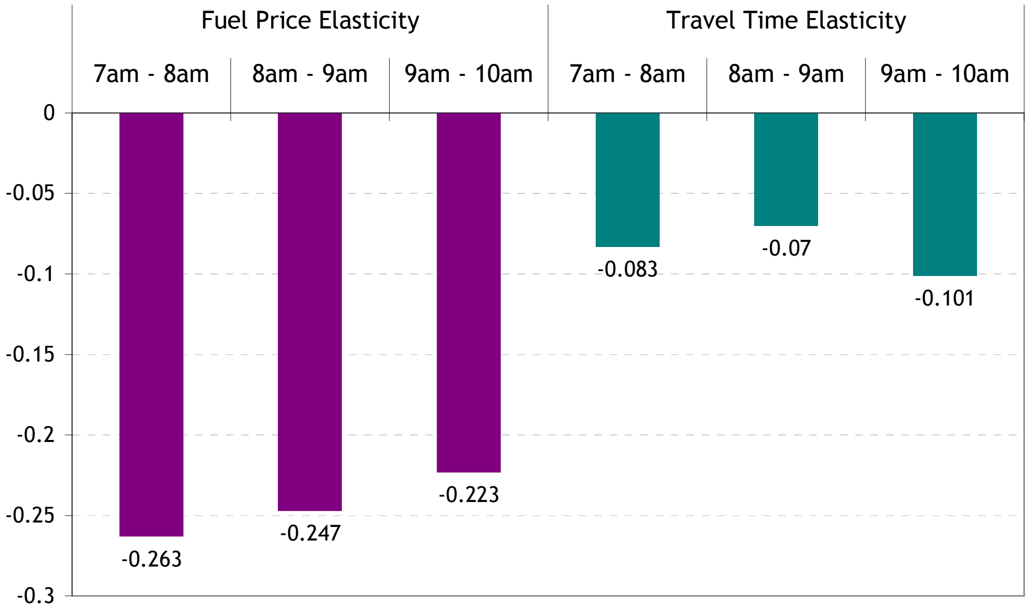
RMSWE =0.392

APPENDIX: FIGURE B2.4 **HOME TO BUSINESS HIGHWAY DEMAND (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR**



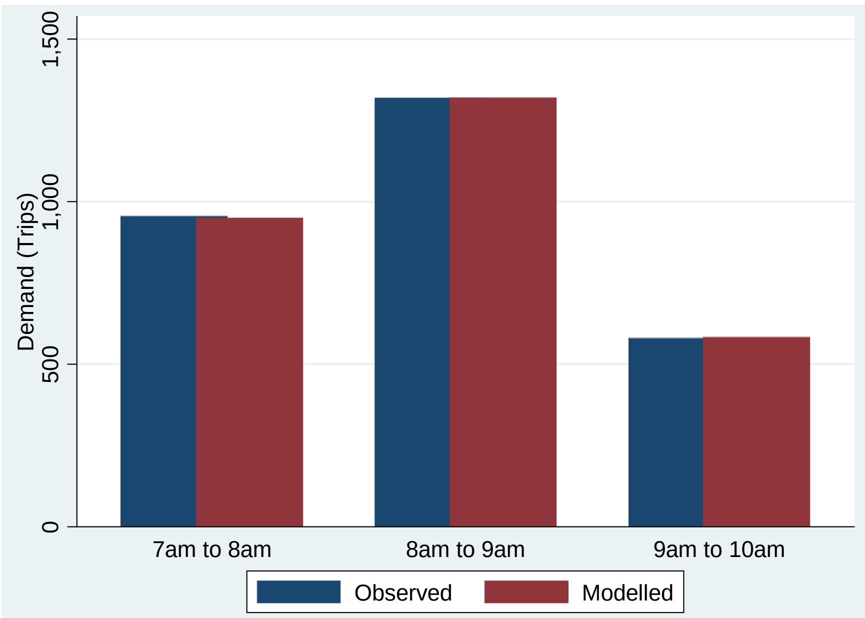
RMSWE =0.255

APPENDIX: FIGURE B2.5 HOME TO BUSINESS HIGHWAY IMPLIED ELASTICITY VALUES

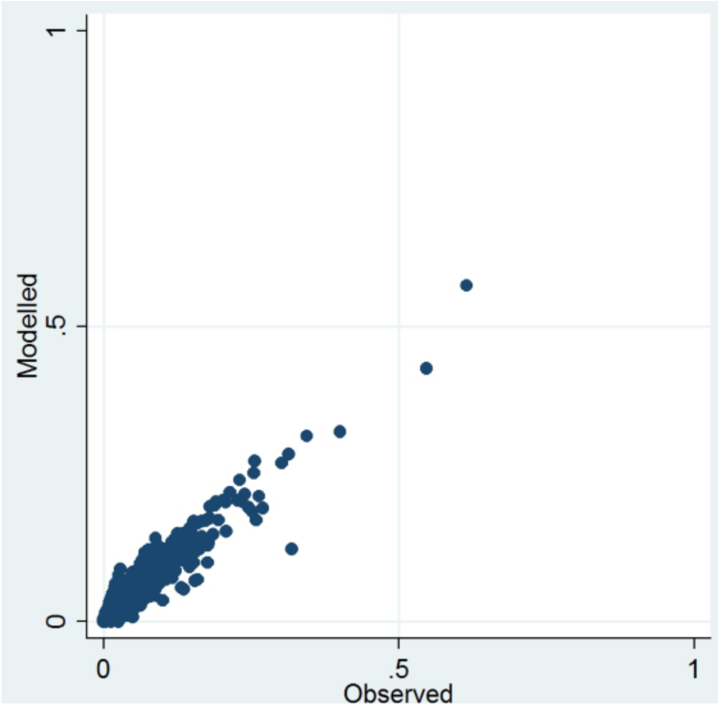


PT Trips

APPENDIX: FIGURE B2.6 HOME TO BUSINESS PT TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME

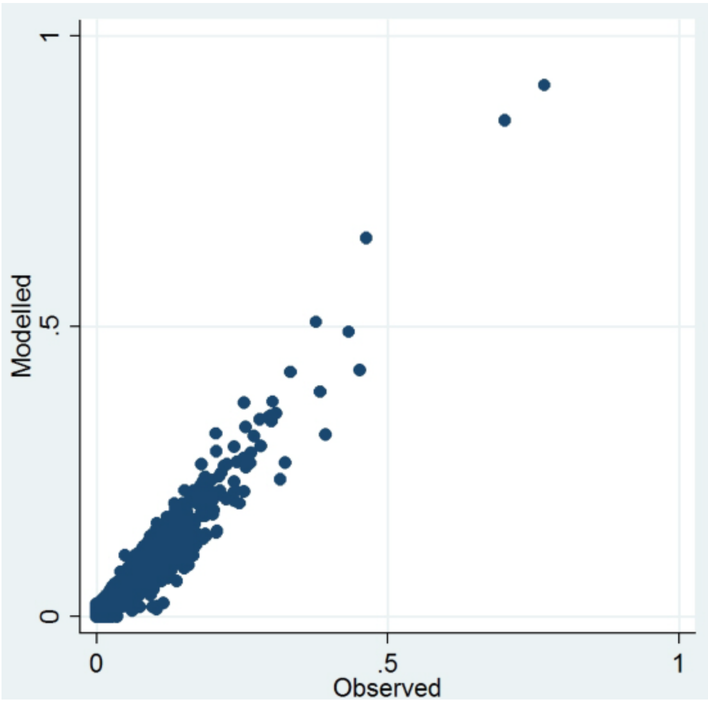


APPENDIX: FIGURE B2.7 **HOME TO BUSINESS PT TRIPS (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR**



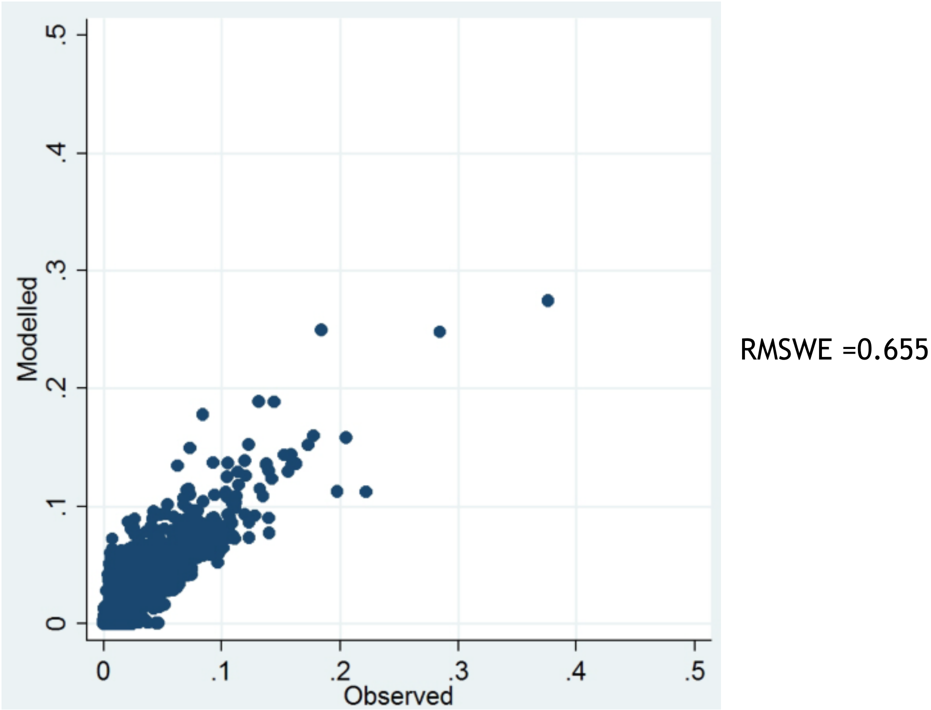
RMSWE =0.315

APPENDIX: FIGURE B2.8 **HOME TO BUSINESS PT TRIPS (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR**



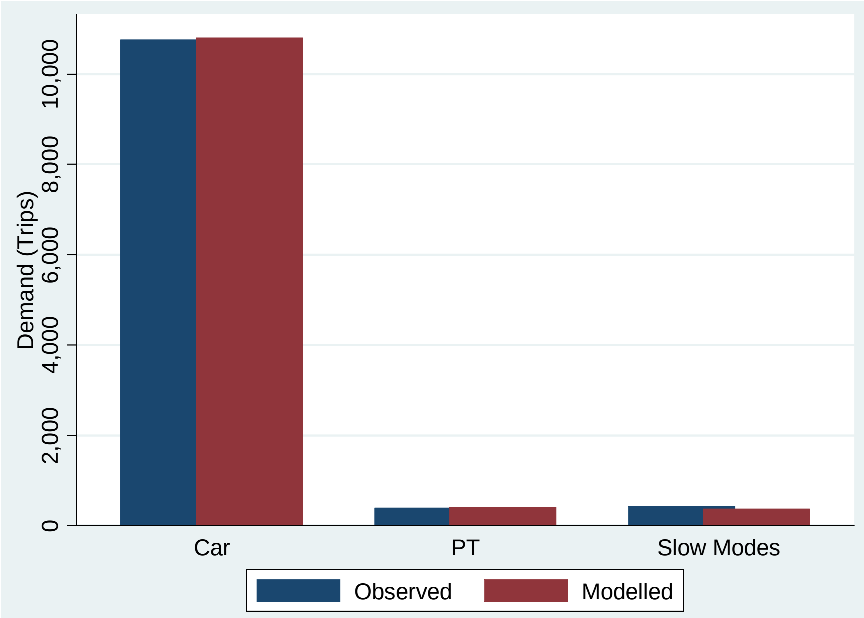
RMSWE =0.299

APPENDIX: FIGURE B2.9 **HOME TO BUSINESS PT TRIPS (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR**

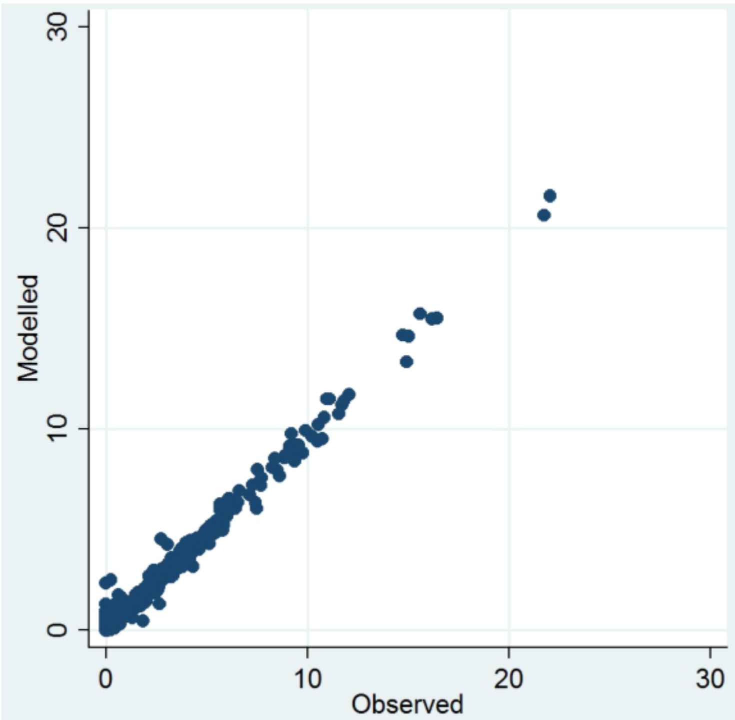


APPENDIX: FIGURE B2.10 **HOME TO BUSINESS PT IMPLIED ELASTICITY VALUES**

APPENDIX: FIGURE B2.11 HOME TO BUSINESS CAR AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE

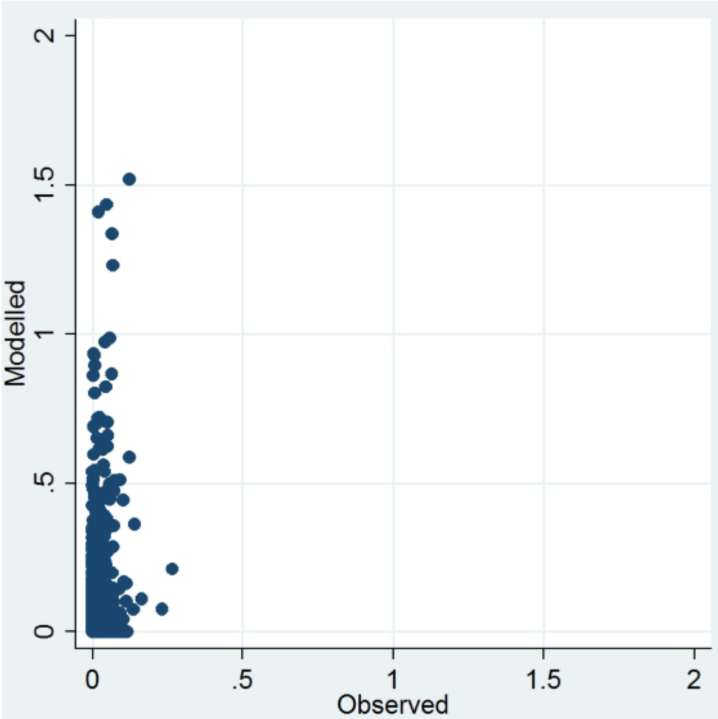


APPENDIX: FIGURE B2.12 HOME TO BUSINESS CAR AVAILABLE HIGHWAY DEMAND: MODELLED V OBSERVED BY OD PAIR



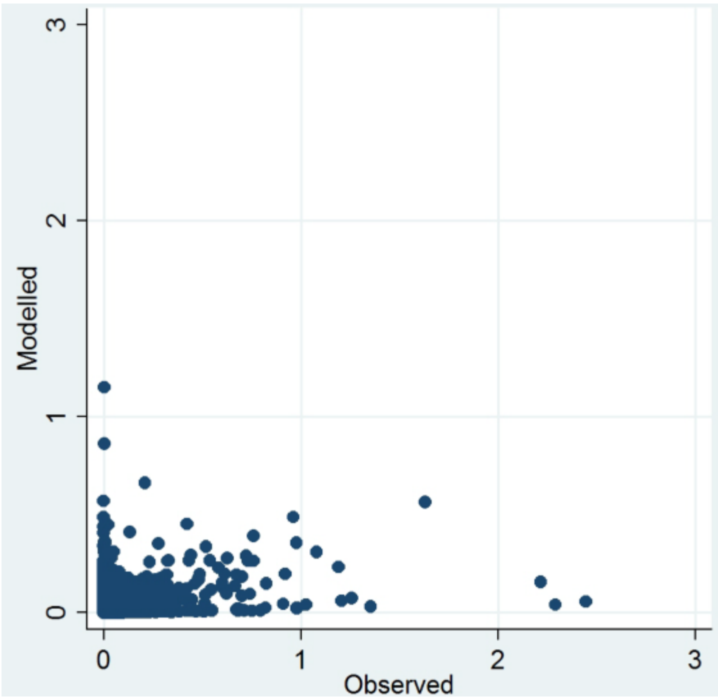
RMSWE =0.976

APPENDIX: FIGURE B2.13 **HOME TO BUSINESS CAR AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR**



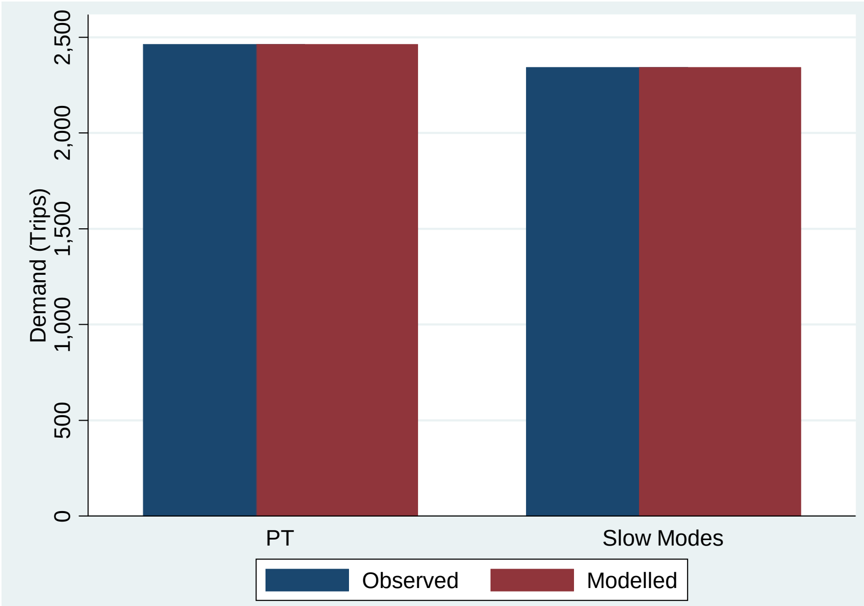
RMSWE =9.015

APPENDIX: FIGURE B2.14 **HOME TO BUSINESS CAR AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR**

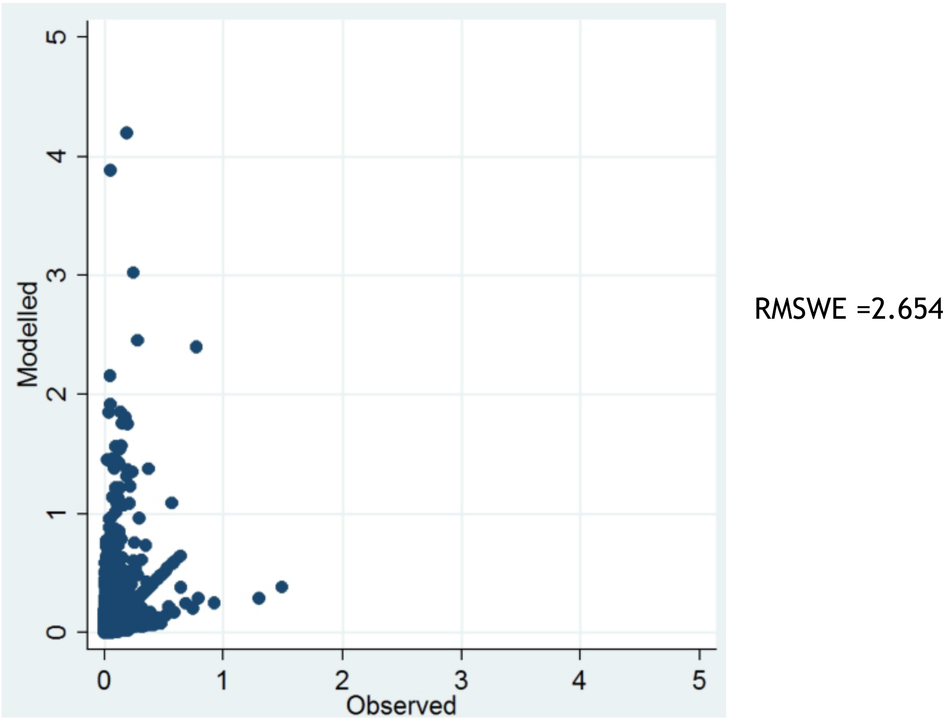


RMSWE =2.618

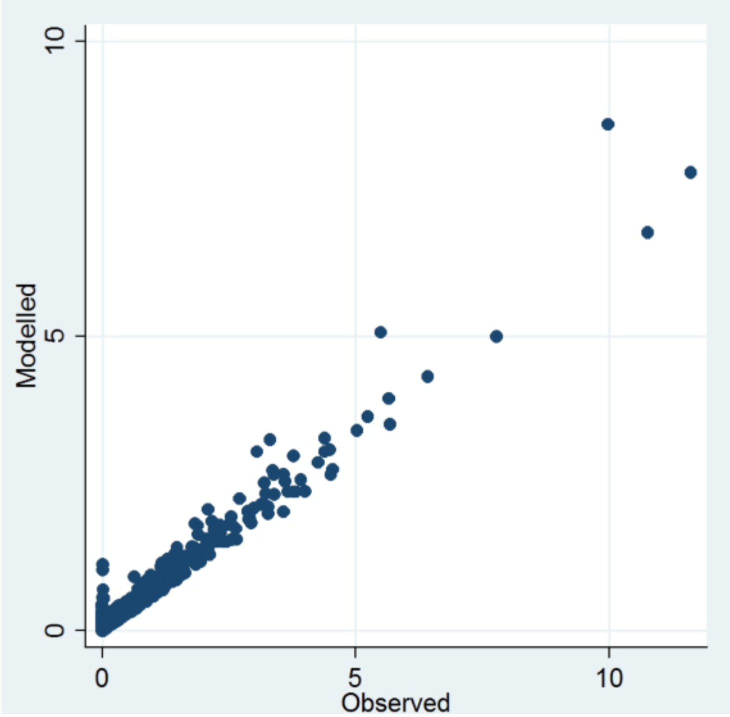
APPENDIX: FIGURE B2.15 HOME TO BUSINESS CAR NON-AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE



APPENDIX: FIGURE B2.16 HOME TO BUSINESS CAR NON-AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR



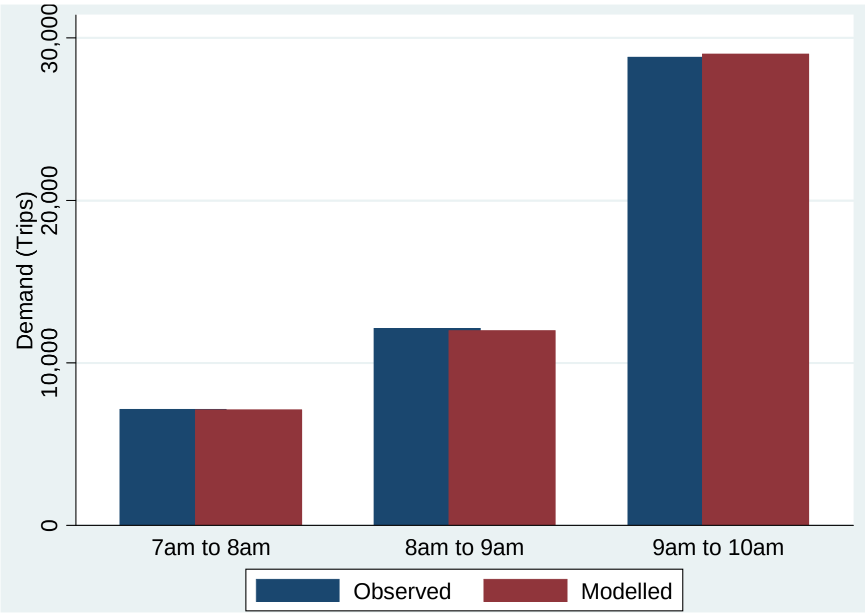
APPENDIX: FIGURE B2.17 **HOME TO BUSINESS CAR NON-AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR**



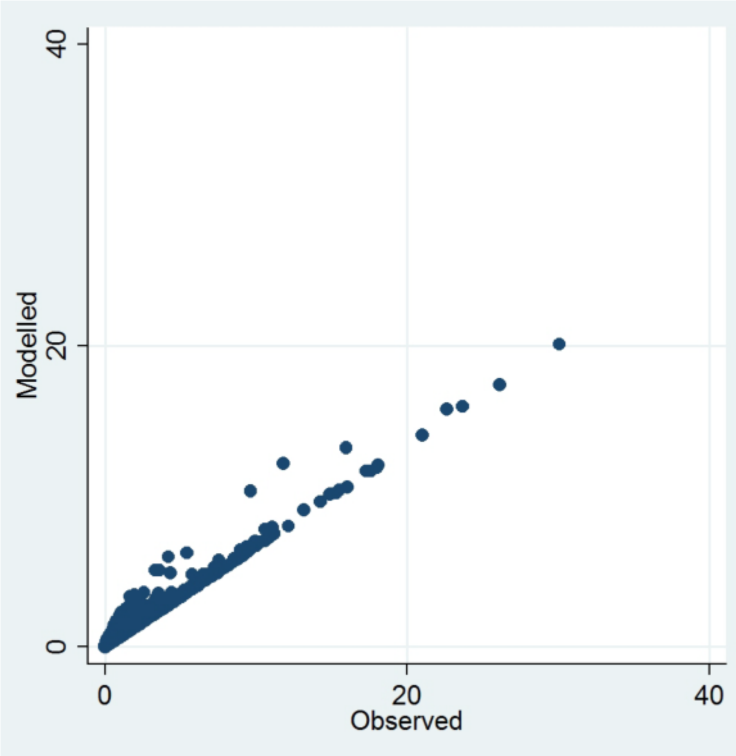
RMSWE =0.833

B3. HOME TO OTHER

APPENDIX: FIGURE B3.1 HOME TO OTHER HIGHWAY TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME

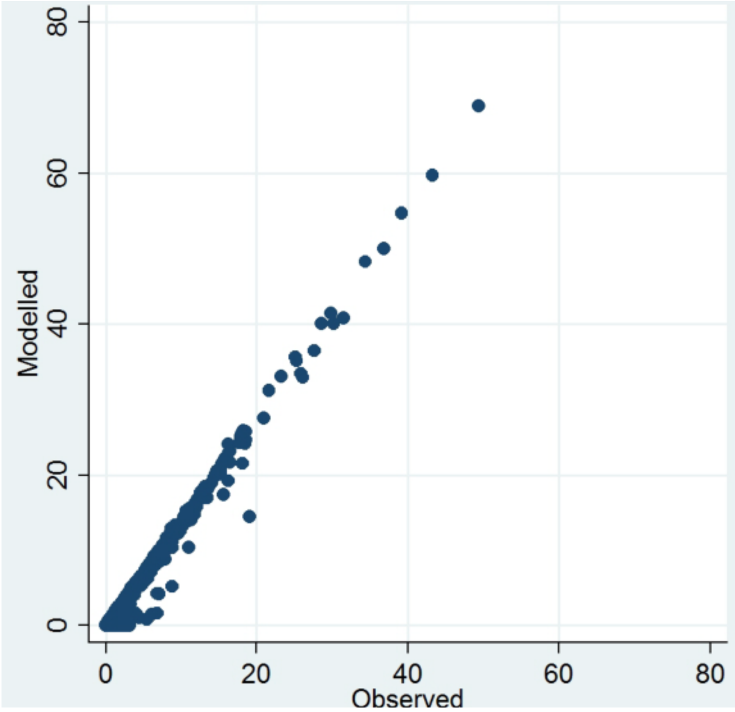


APPENDIX: FIGURE B3.2 HOME TO OTHER HIGHWAY TRIPS (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR



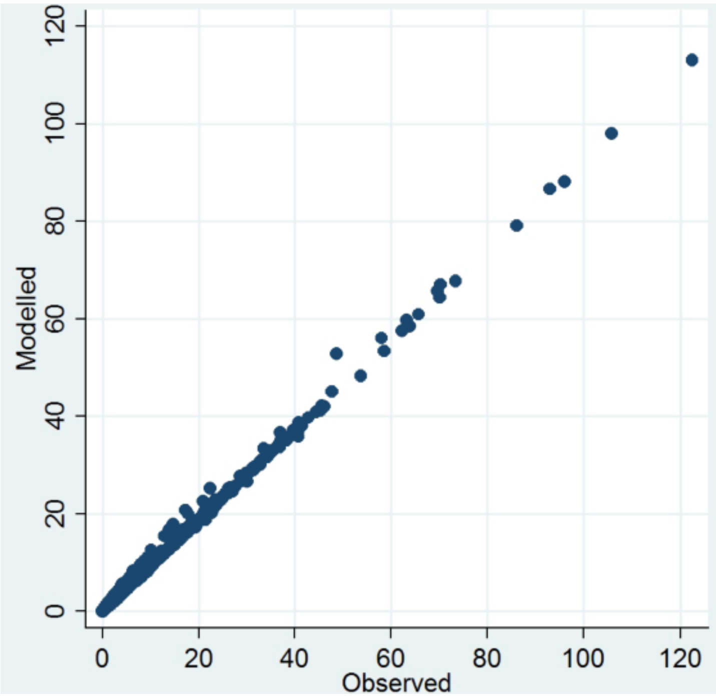
RMSWE =0.453

APPENDIX: FIGURE B3.3 HOME TO OTHER HIGHWAY TRIPS (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR



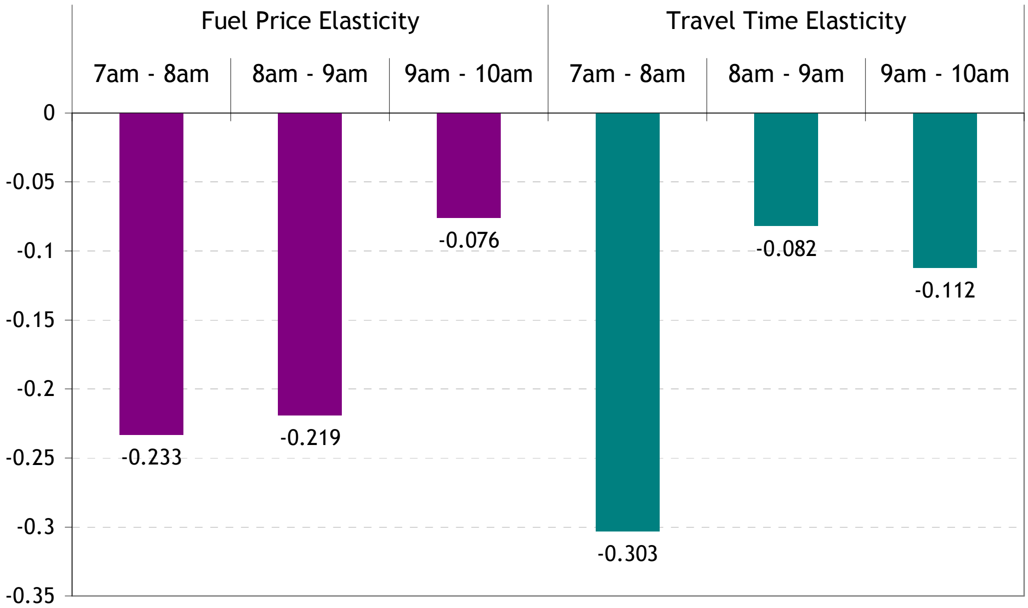
RMSWE =0.488

APPENDIX: FIGURE B3.4 HOME TO OTHER HIGHWAY TRIPS (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR

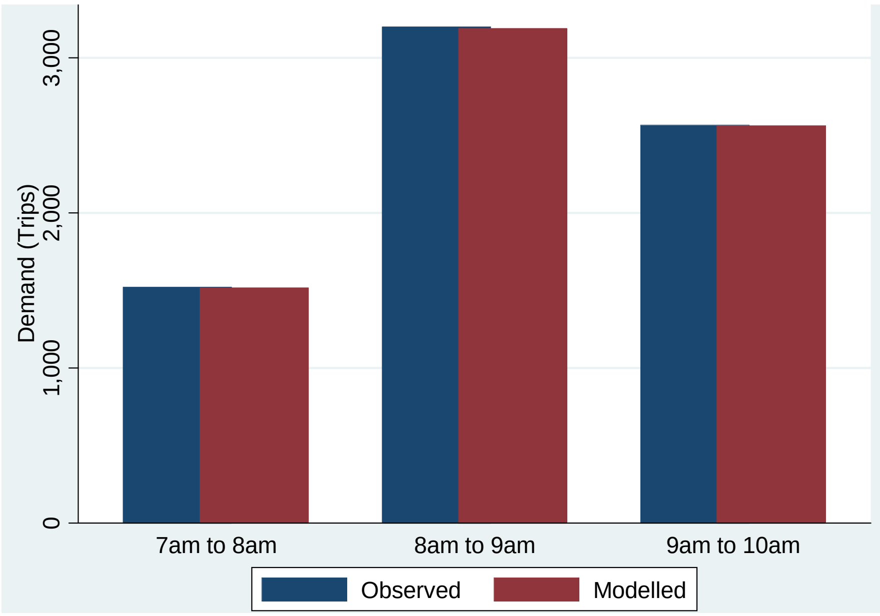


RMSWE =0.110

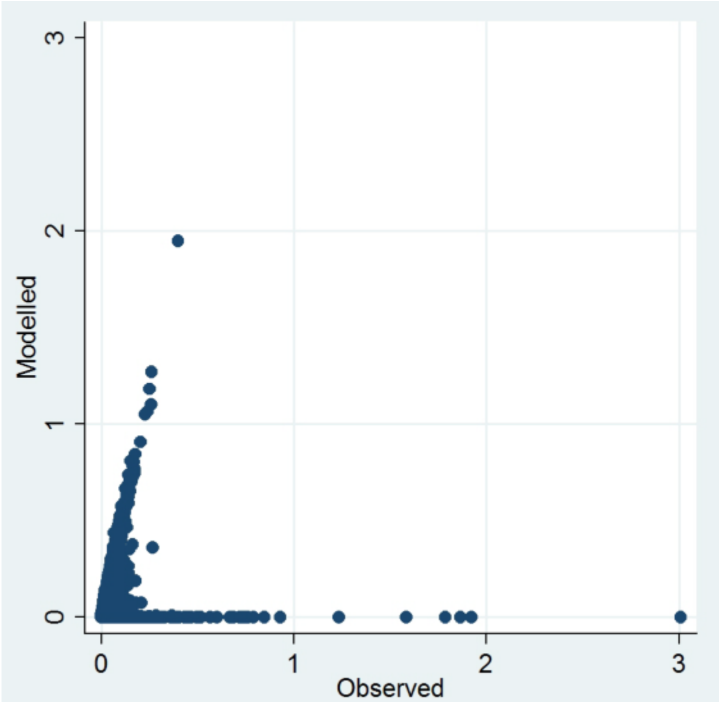
APPENDIX: FIGURE B3.5 **HOME TO OTHER HIGHWAY IMPLIED ELASTICITY VALUES**



APPENDIX: FIGURE B3.6 **HOME TO OTHER PT TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME**

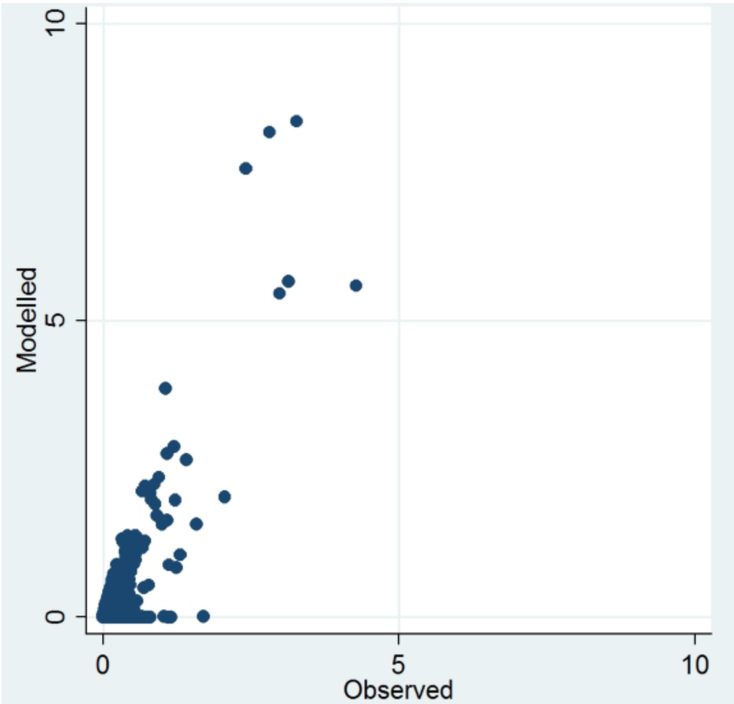


APPENDIX: FIGURE B3.7 HOME TO OTHER PT TRIPS (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR



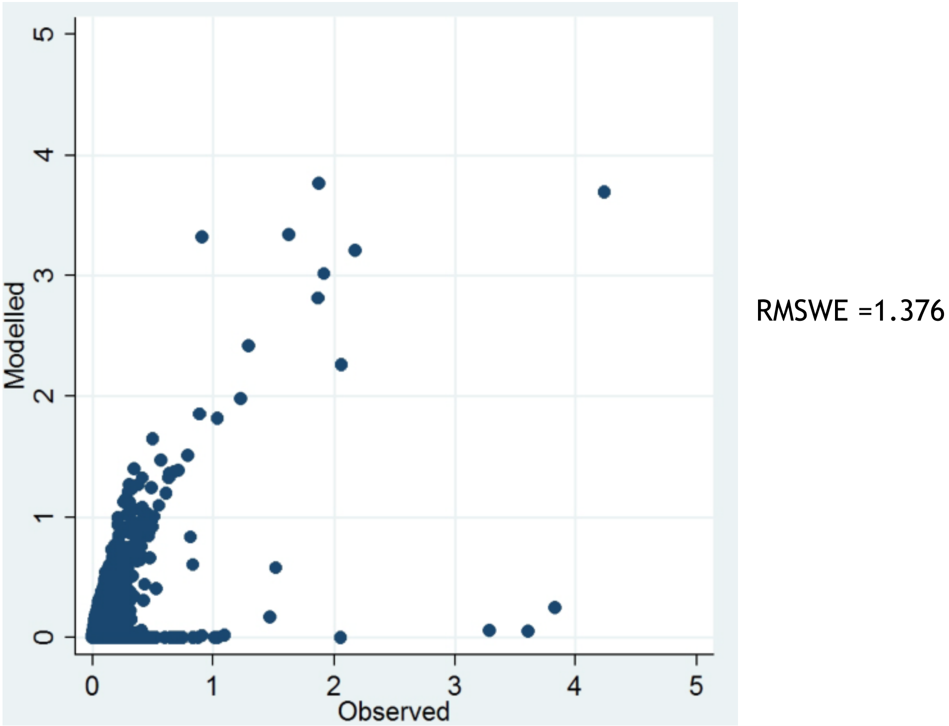
RMSWE =1.872

APPENDIX: FIGURE B3.8 HOME TO OTHER PT TRIPS (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR



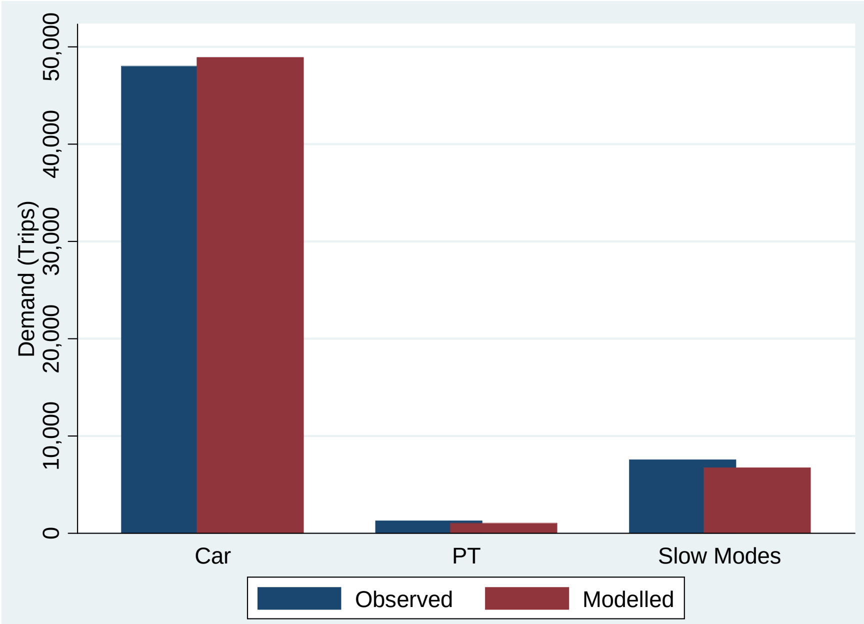
RMSWE =1.170

APPENDIX: FIGURE B3.9 **HOME TO OTHER PT TRIPS (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR**

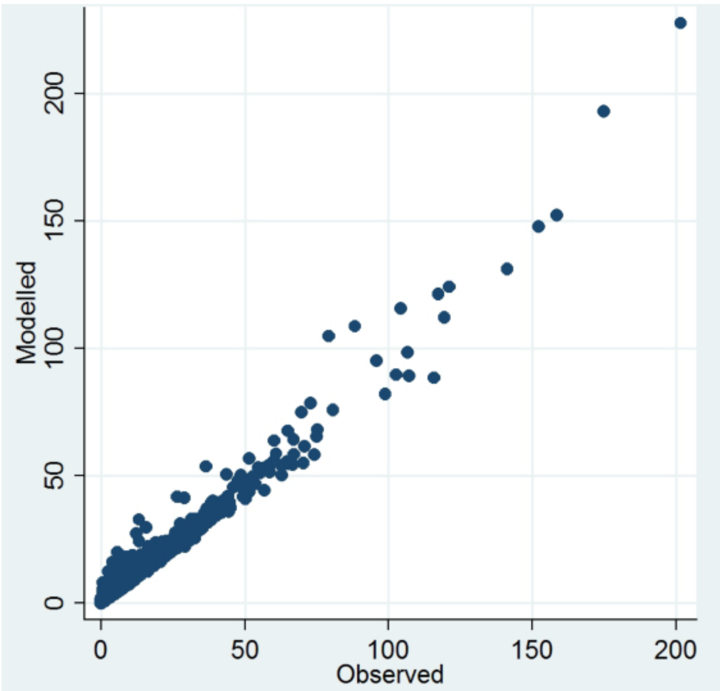


APPENDIX: FIGURE B3.10 **HOME TO OTHER PT IMPLIED ELASTICITY VALUES**

APPENDIX: FIGURE B3.11 HOME TO OTHER CAR AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE

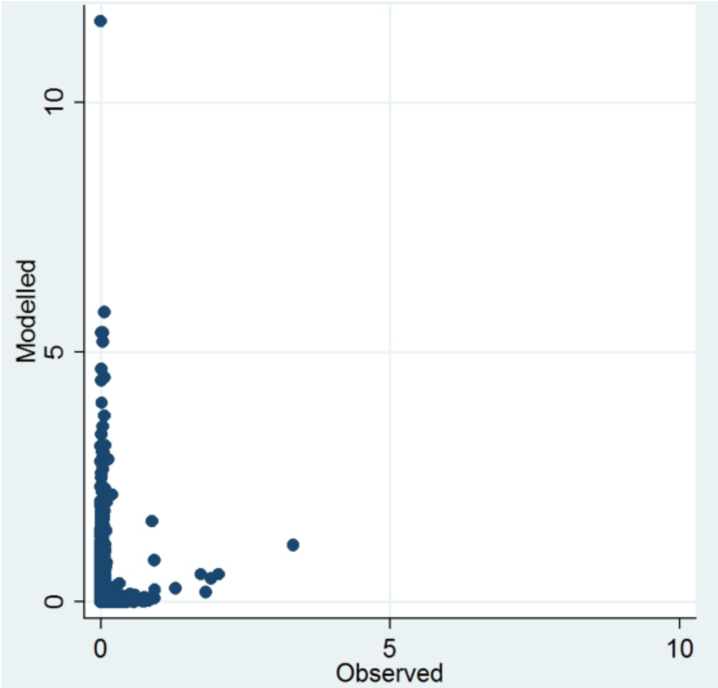


APPENDIX: FIGURE B3.12 HOME TO OTHER CAR AVAILABLE HIGHWAY DEMAND: MODELLED V OBSERVED BY OD PAIR



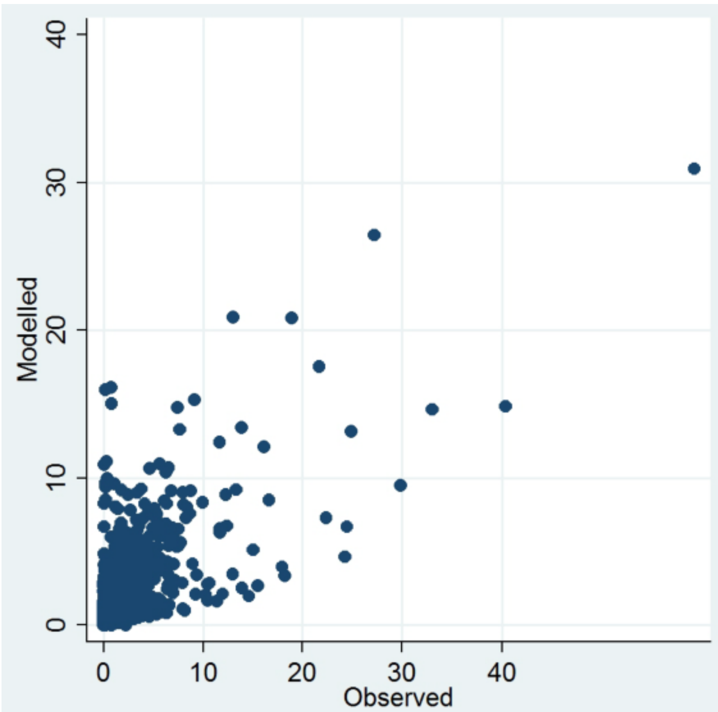
RMSWE =0.406

APPENDIX: FIGURE B3.13 **HOME TO OTHER CAR AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR**



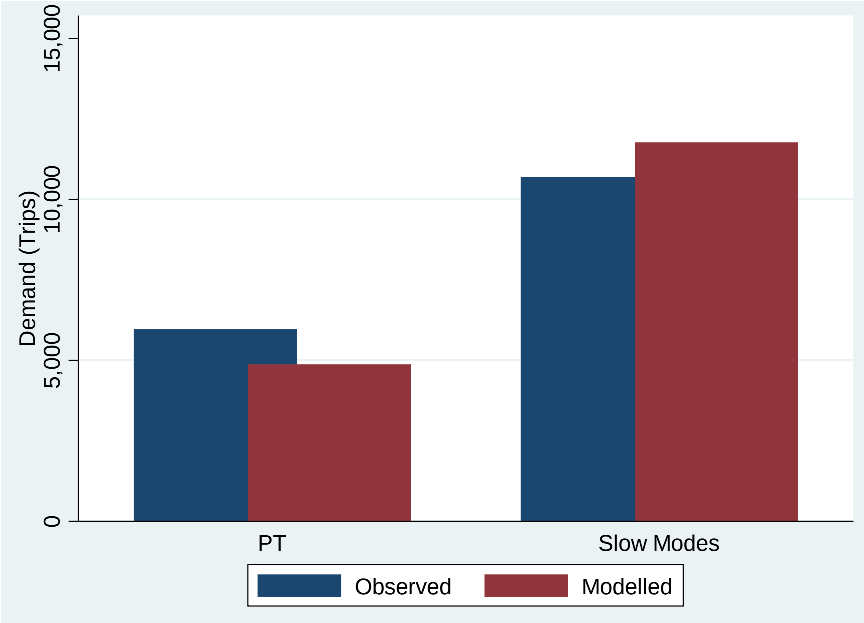
RMSWE =14.337

APPENDIX: FIGURE B3.14 **HOME TO OTHER CAR AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR**

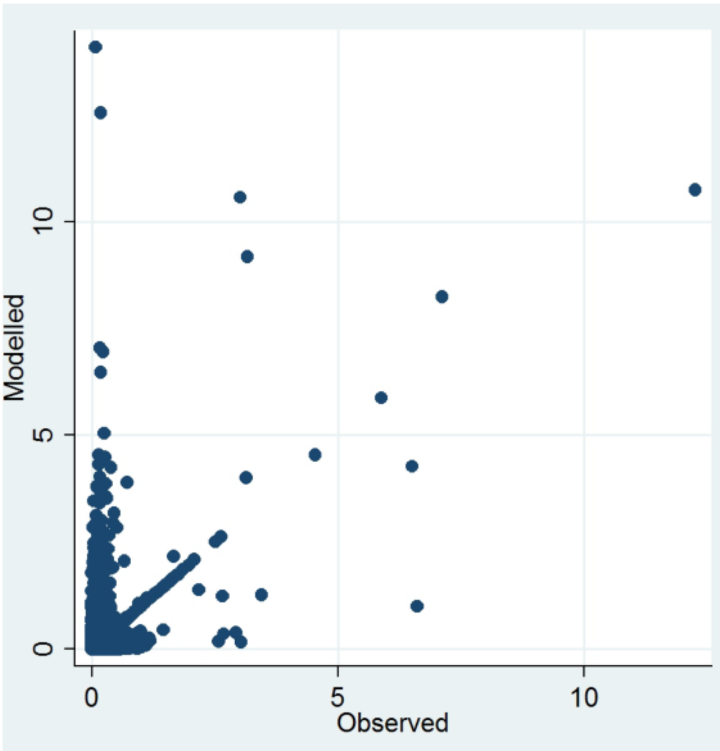


RMSWE =1.947

APPENDIX: FIGURE B3.15 HOME TO OTHER CAR NON-AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE



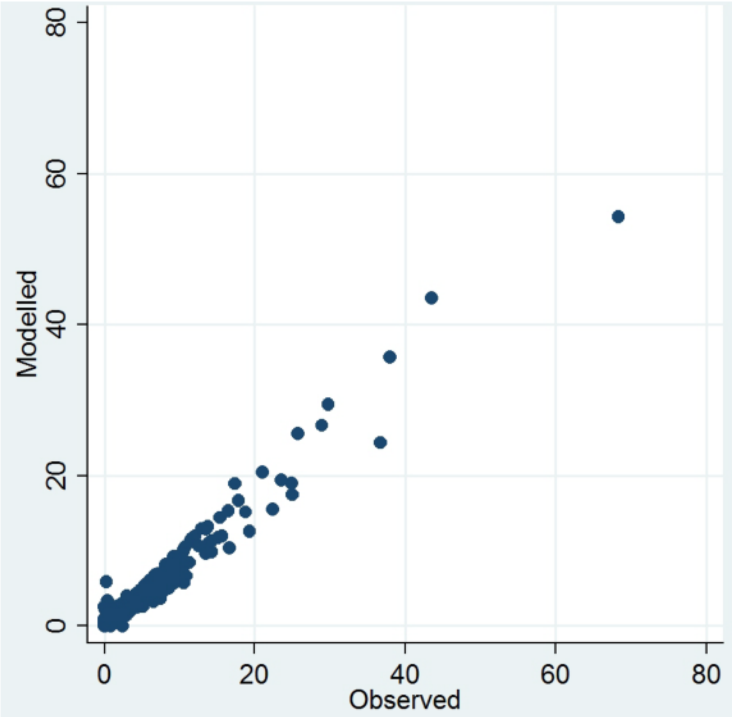
APPENDIX: FIGURE B3.16 HOME TO OTHER CAR NON-AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR



RMSWE =2.330

0	0	0

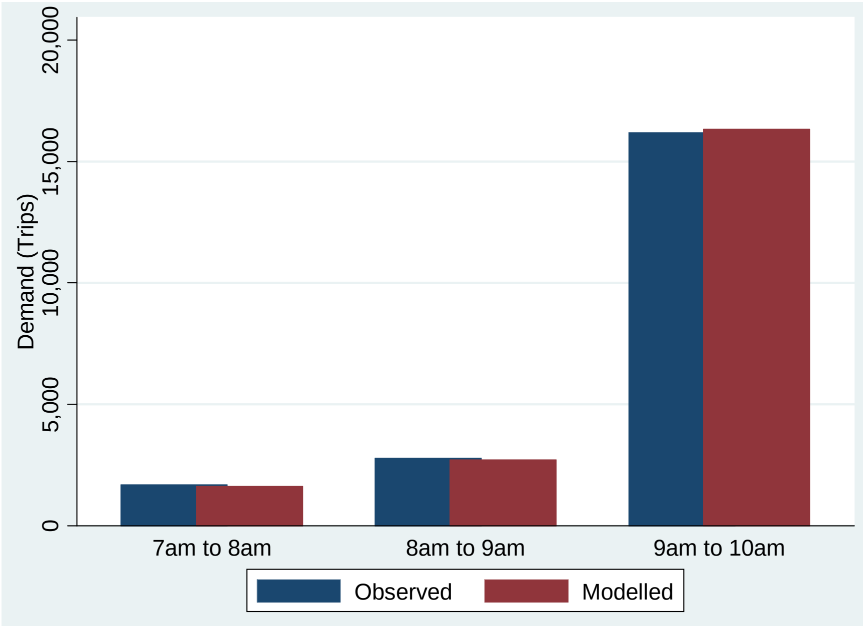
APPENDIX: FIGURE B3.17 HOME TO OTHER CAR NON-AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR



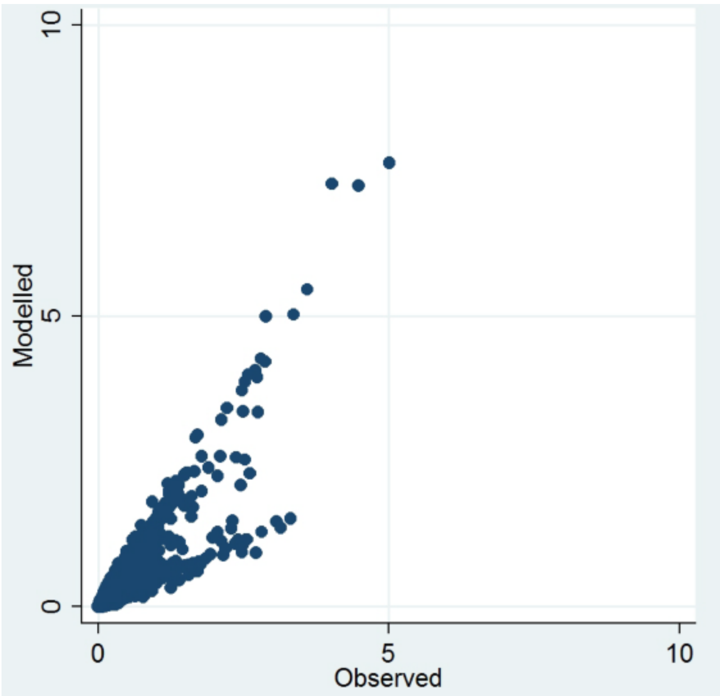
RMSWE =1.068

B4. HOME TO SHOP

APPENDIX: FIGURE B4.1 HOME TO SHOP HIGHWAY TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME

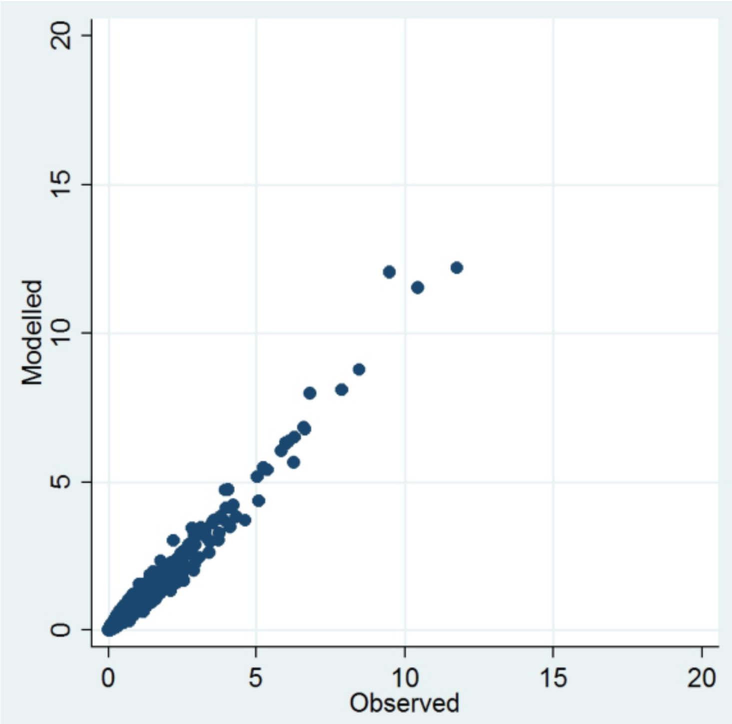


APPENDIX: FIGURE B4.2 HOME TO SHOP HIGHWAY TRIPS (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR



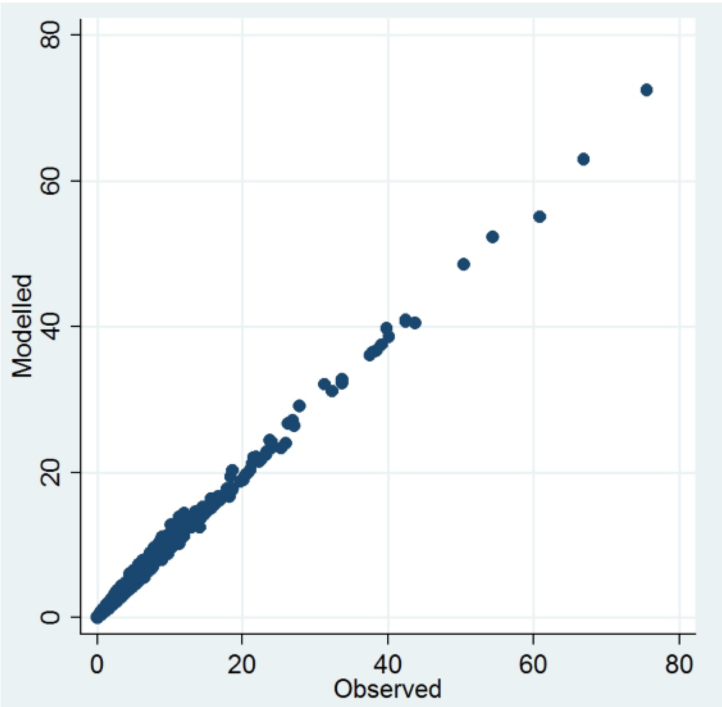
RMSWE =0.560

APPENDIX: FIGURE B4.3 HOME TO SHOP HIGHWAY TRIPS (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR



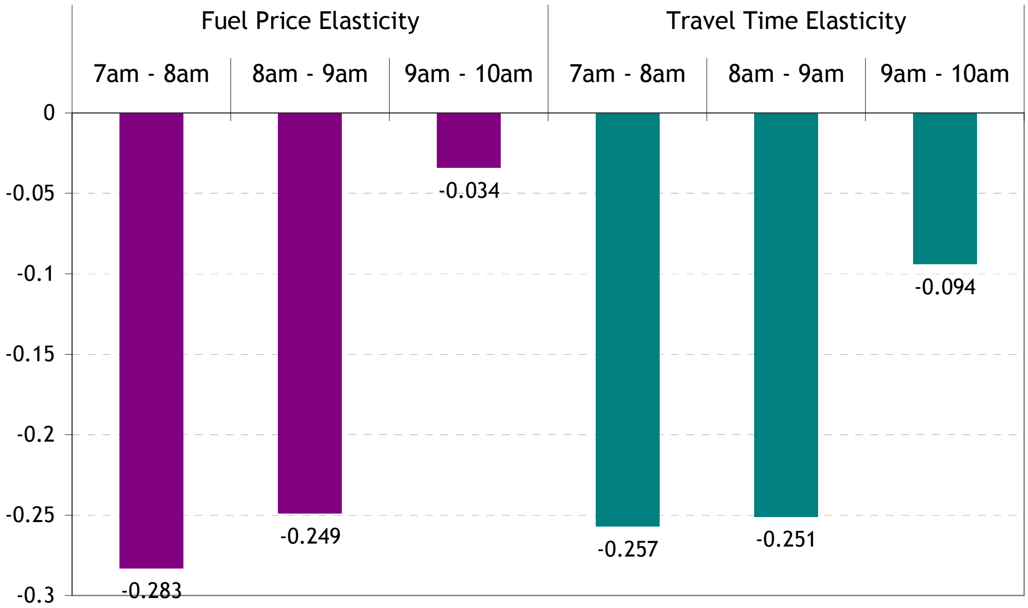
RMSWE =0.229

APPENDIX: FIGURE B4.4 HOME TO SHOP HIGHWAY TRIPS (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR

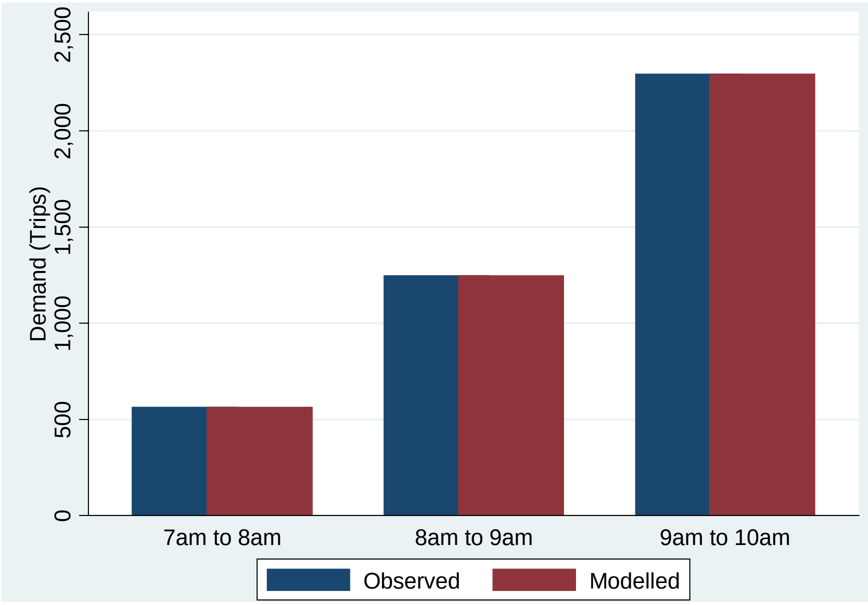


RMSWE =0.111

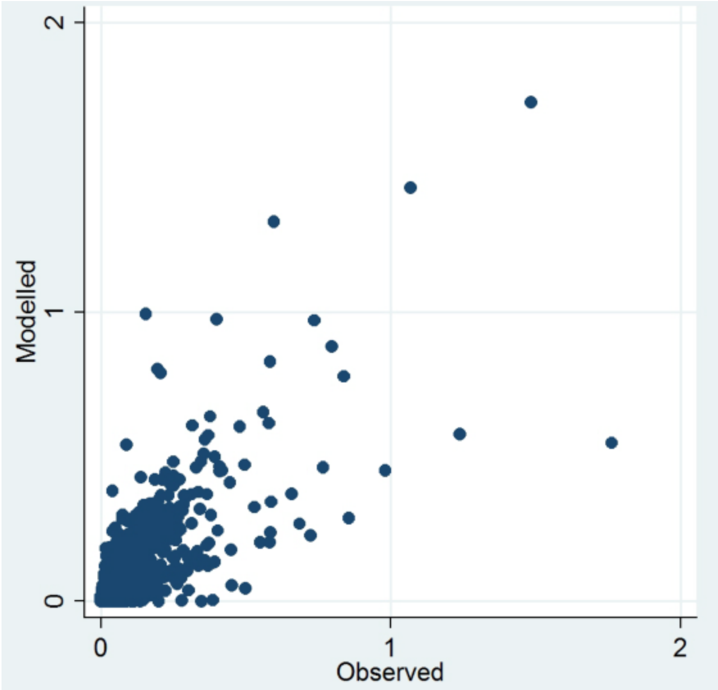
APPENDIX: FIGURE B4.5 HOME TO SHOP HIGHWAY IMPLIED ELASTICITY VALUES



APPENDIX: FIGURE B4.6 HOME TO SHOP PT TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME

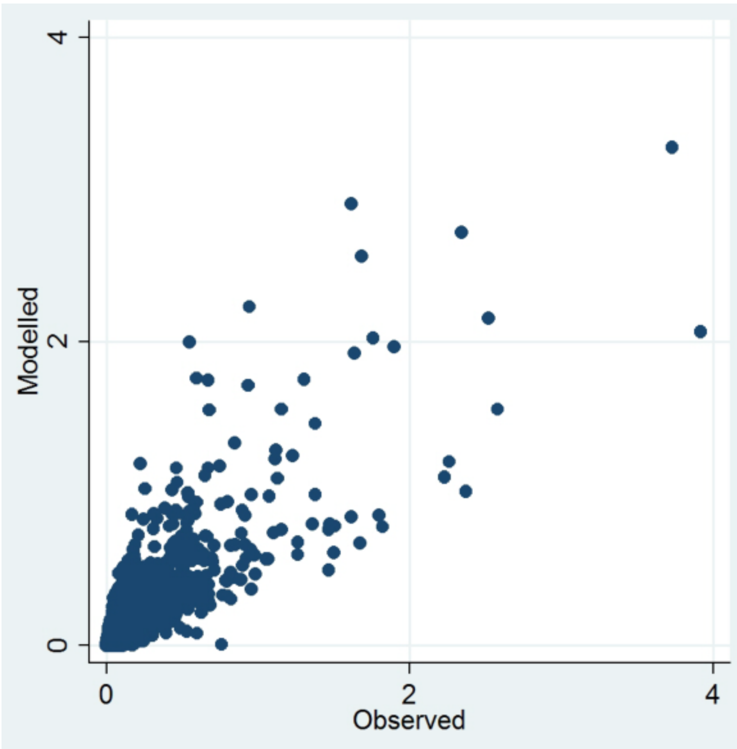


APPENDIX: FIGURE B4.7 HOME TO SHOP PT TRIPS (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR



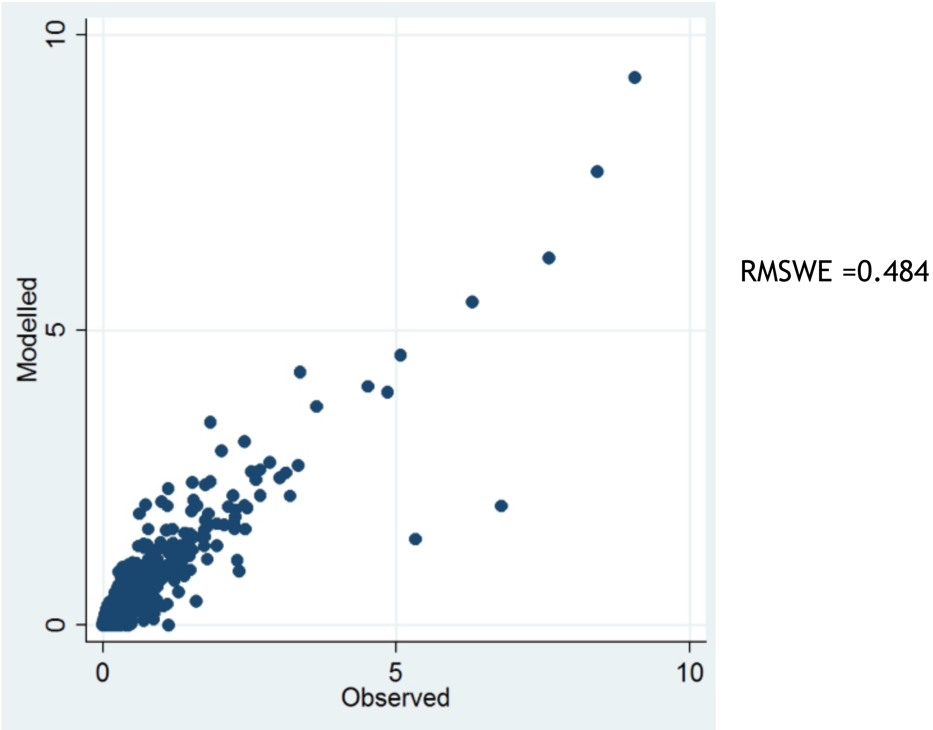
RMSWE =0.741

APPENDIX: FIGURE B4.8 HOME TO SHOP PT TRIPS (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR



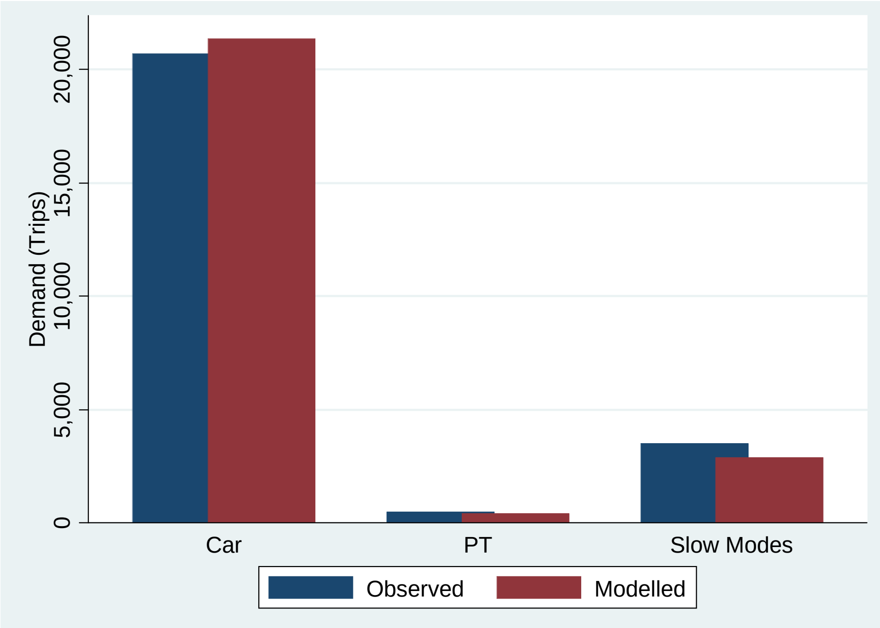
RMSWE =0.629

APPENDIX: FIGURE B4.9 HOME TO SHOP PT TRIPS (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR

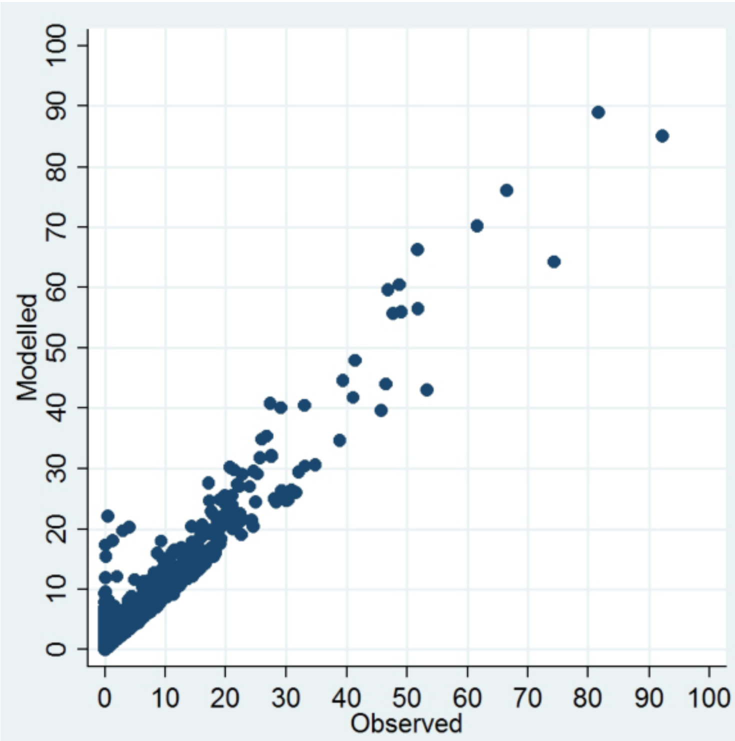


APPENDIX: FIGURE B4.10 HOME TO SHOP PT IMPLIED ELASTICITY VALUES

APPENDIX: FIGURE B4.11 **HOME TO SHOP CAR AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE**

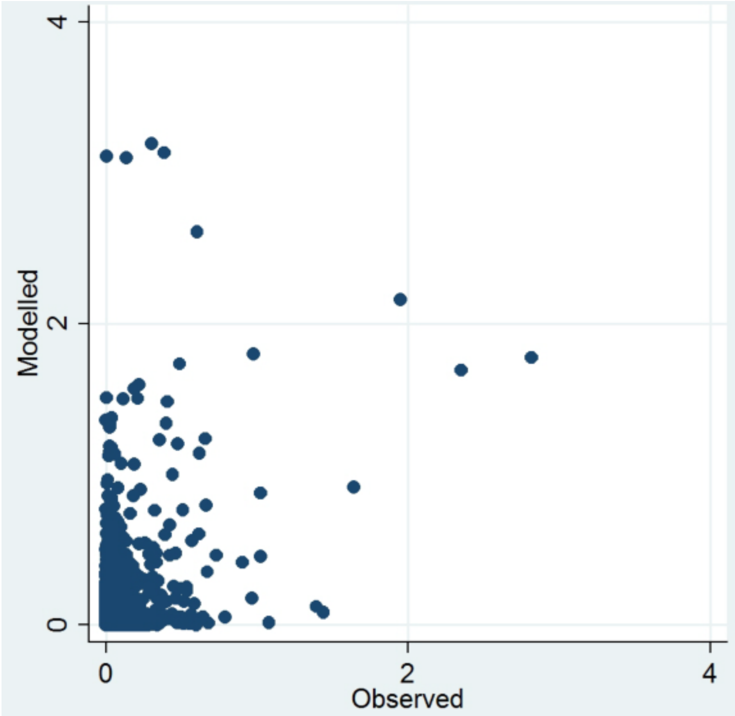


APPENDIX: FIGURE B4.12 **HOME TO SHOP CAR AVAILABLE HIGHWAY DEMAND: MODELLED V OBSERVED BY OD PAIR**



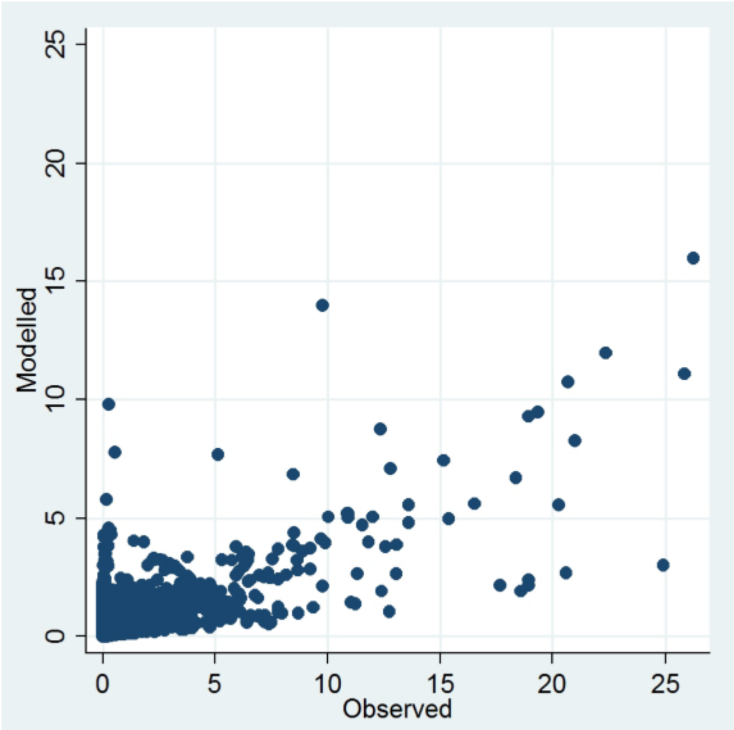
RMSWE =2.322

APPENDIX: FIGURE B4.13 HOME TO SHOP CAR AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR



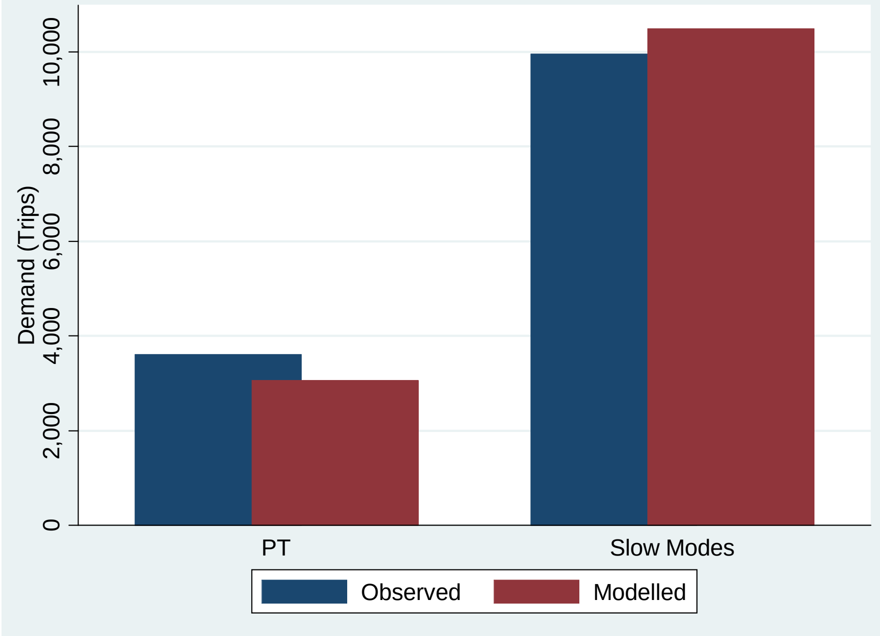
RMSWE =7.996

APPENDIX: FIGURE B4.14 HOME TO SHOP CAR AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR

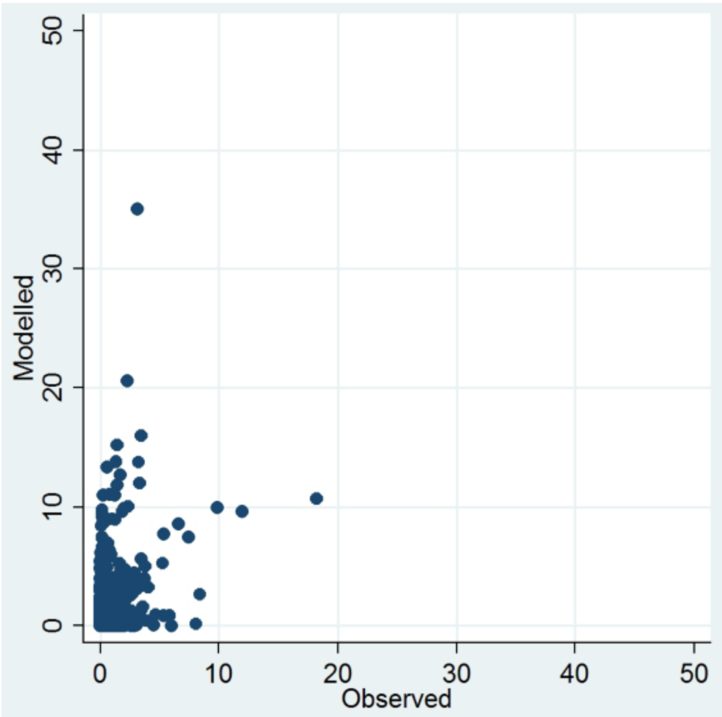


RMSWE =2.947

APPENDIX: FIGURE B4.15 HOME TO SHOP CAR NON-AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE

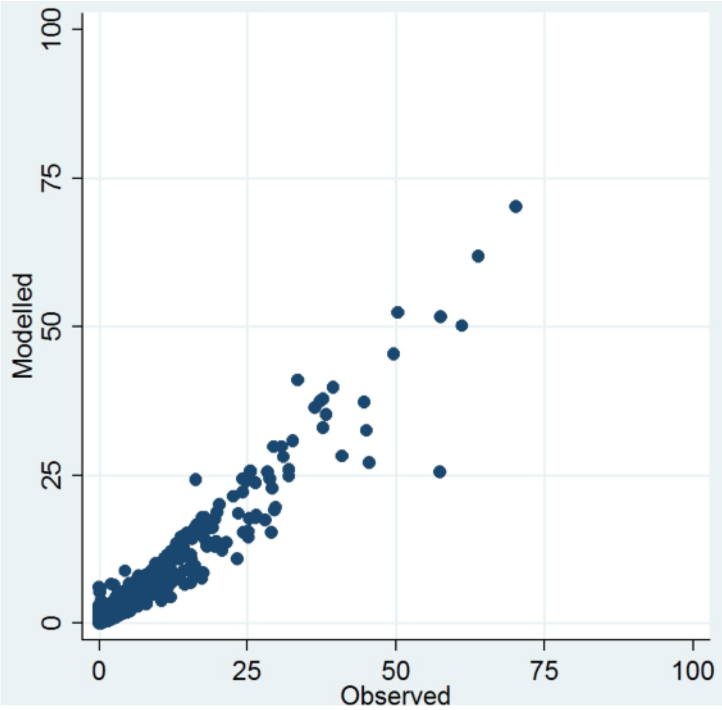


APPENDIX: FIGURE B4.16 HOME TO SHOP CAR NON-AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR



RMSWE =5.644

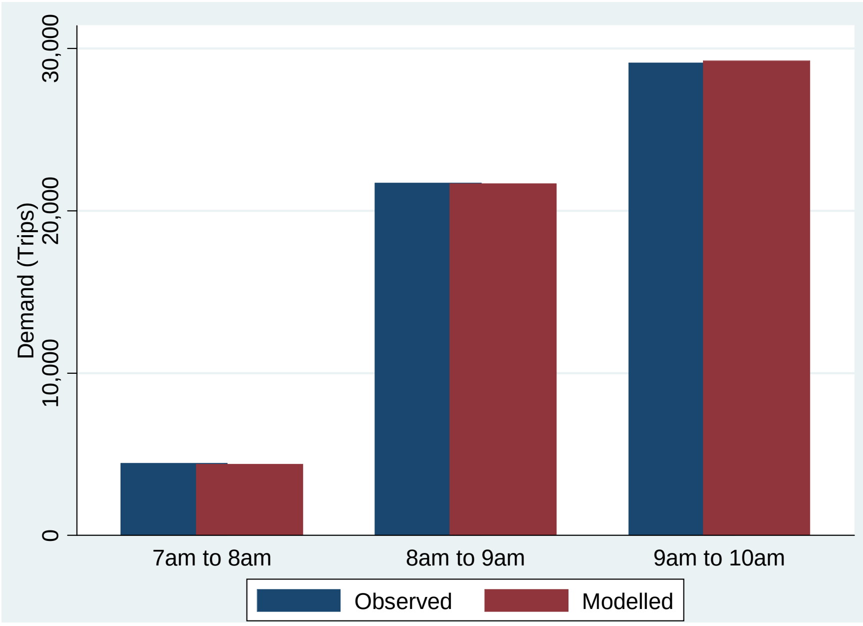
APPENDIX: FIGURE B4.17 HOME TO SHOP CAR NON-AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR



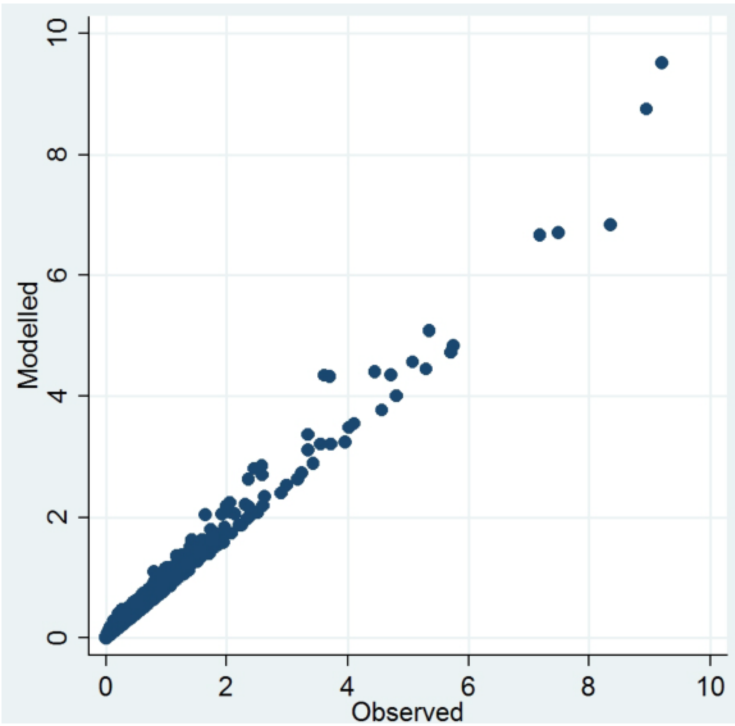
RMSWE =1.377

B5. NON-HOME BASED

APPENDIX: FIGURE B5.1 NON HOME BASED HIGHWAY TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME

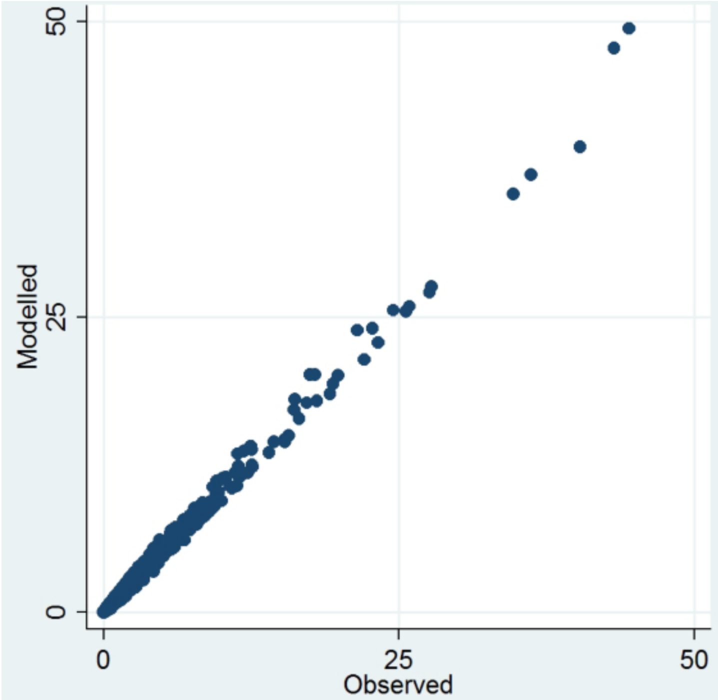


APPENDIX: FIGURE B5.2 NON HOME BASED HIGHWAY TRIPS (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR



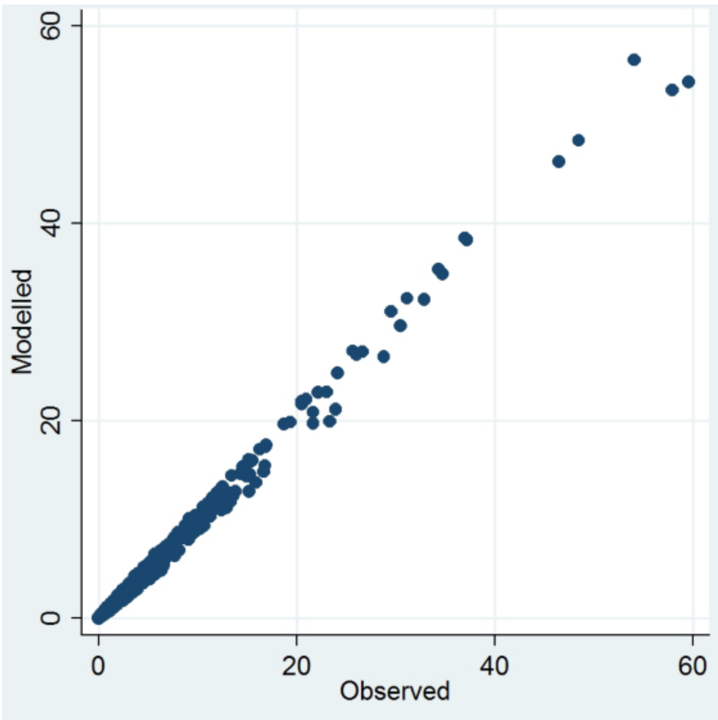
RMSWE =0.180

APPENDIX: FIGURE B5.3 NON HOME BASED HIGHWAY TRIPS (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR



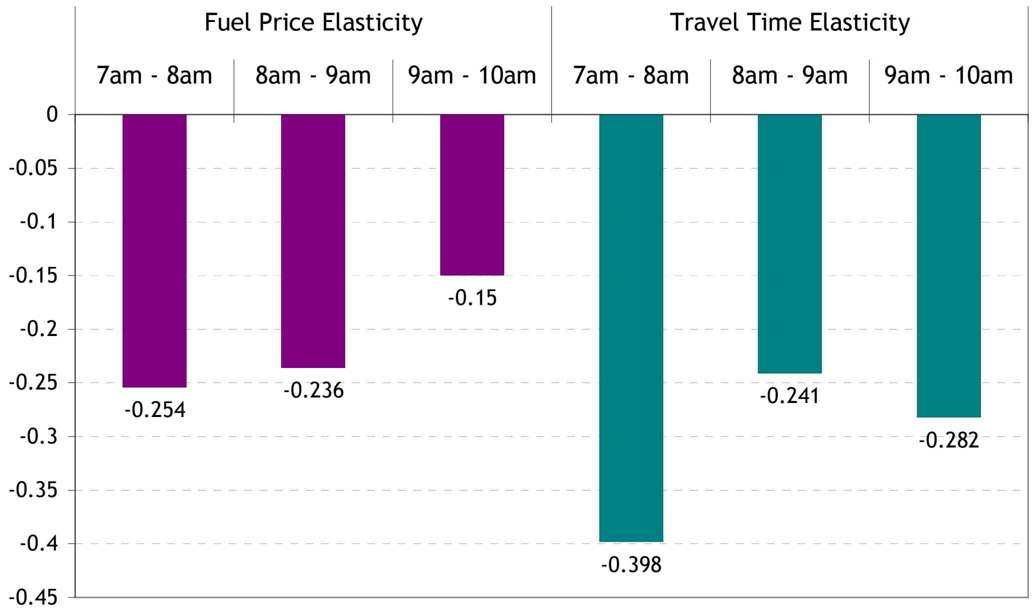
RMSWE =0.105

APPENDIX: FIGURE B5.4 NON HOME BASED HIGHWAY TRIPS (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR

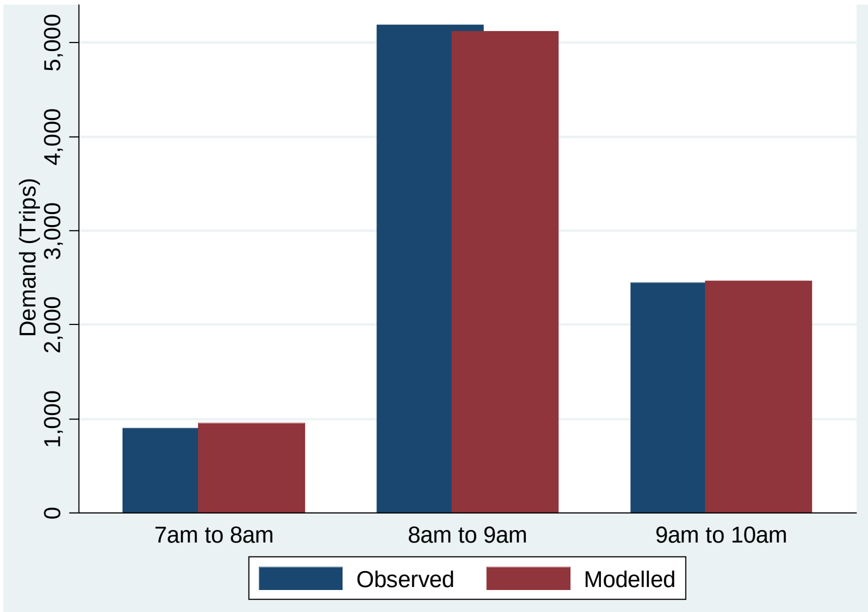


RMSWE =0.085

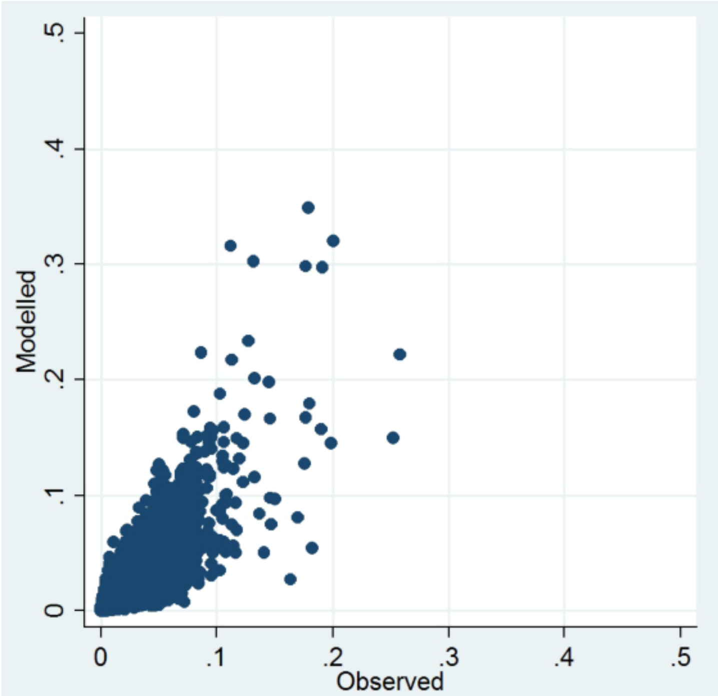
APPENDIX: FIGURE B5.5 NON HOME BASED HIGHWAY IMPLIED ELASTICITY VALUES



APPENDIX: FIGURE B5.6 NON HOME BASED PT TRIPS: MODELLED V OBSERVED BY ARRIVAL TIME

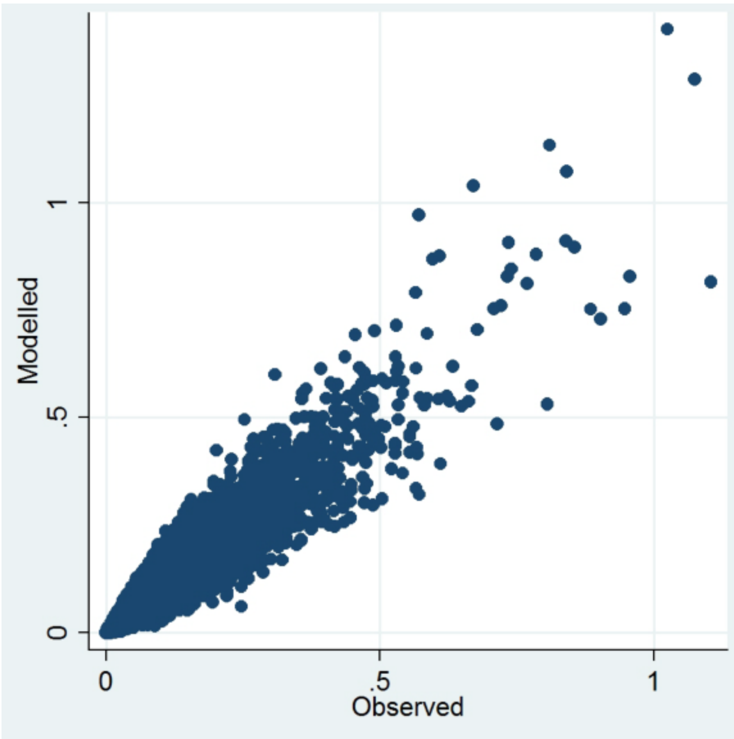


APPENDIX: FIGURE B5.7 **NON HOME BASED PT TRIPS (7AM TO 8AM): MODELLED V OBSERVED BY OD PAIR**



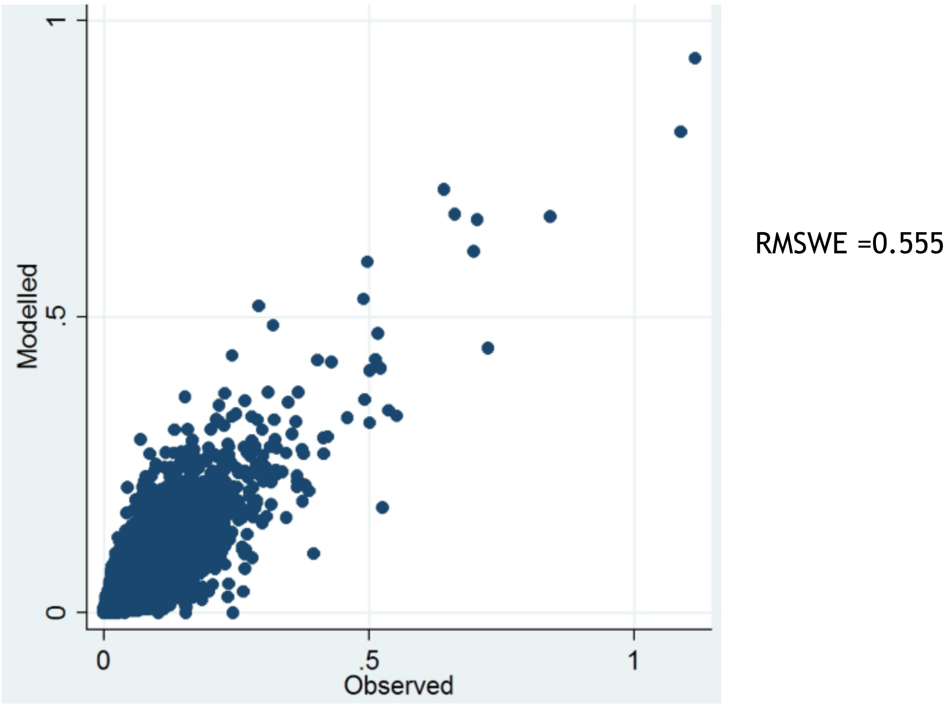
RMSWE =0.405

APPENDIX: FIGURE B5.8 **NON HOME BASED PT TRIPS (8AM TO 9AM): MODELLED V OBSERVED BY OD PAIR**



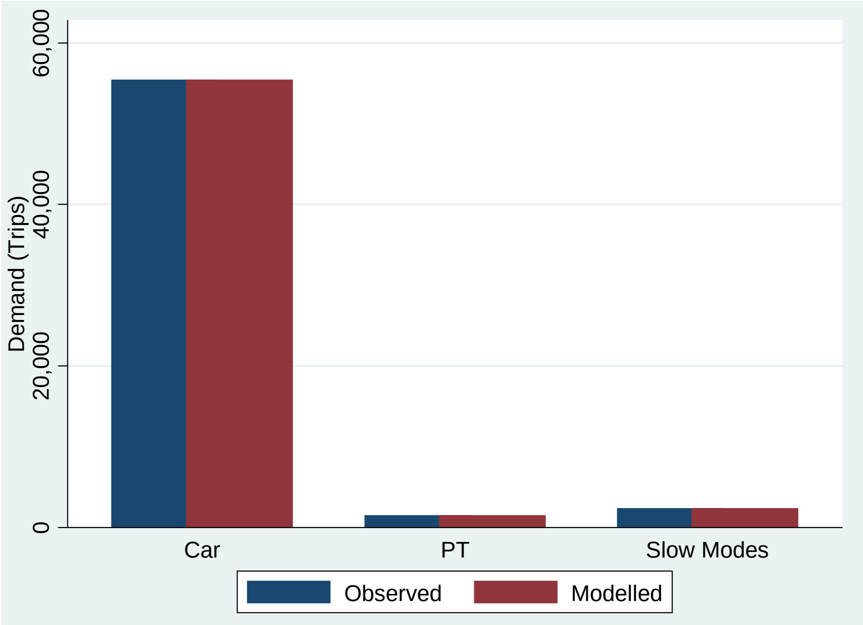
RMSWE =0.281

APPENDIX: FIGURE B5.9 NON HOME BASED PT TRIPS (9AM TO 10AM): MODELLED V OBSERVED BY OD PAIR

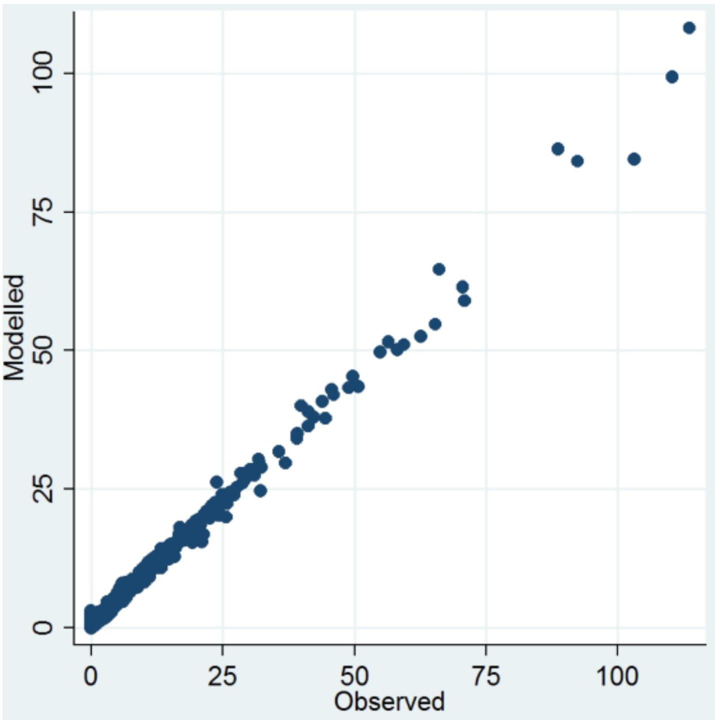


APPENDIX: FIGURE B5.10 NON HOME BASED PT IMPLIED ELASTICITY VALUES

APPENDIX: FIGURE B5.11 **NON HOME BASED CAR AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE**

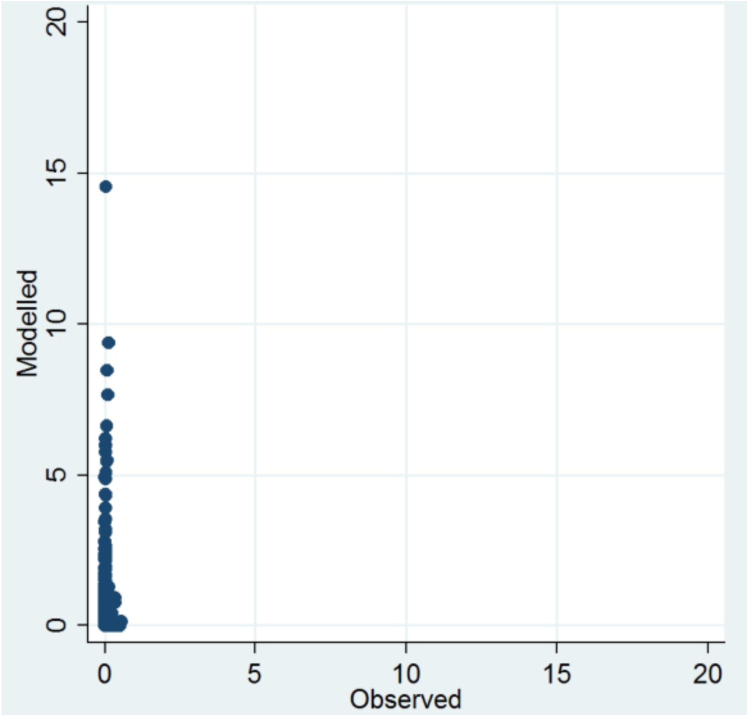


APPENDIX: FIGURE B5.12 **NON HOME BASED CAR AVAILABLE HIGHWAY DEMAND: MODELLED V OBSERVED BY OD PAIR**



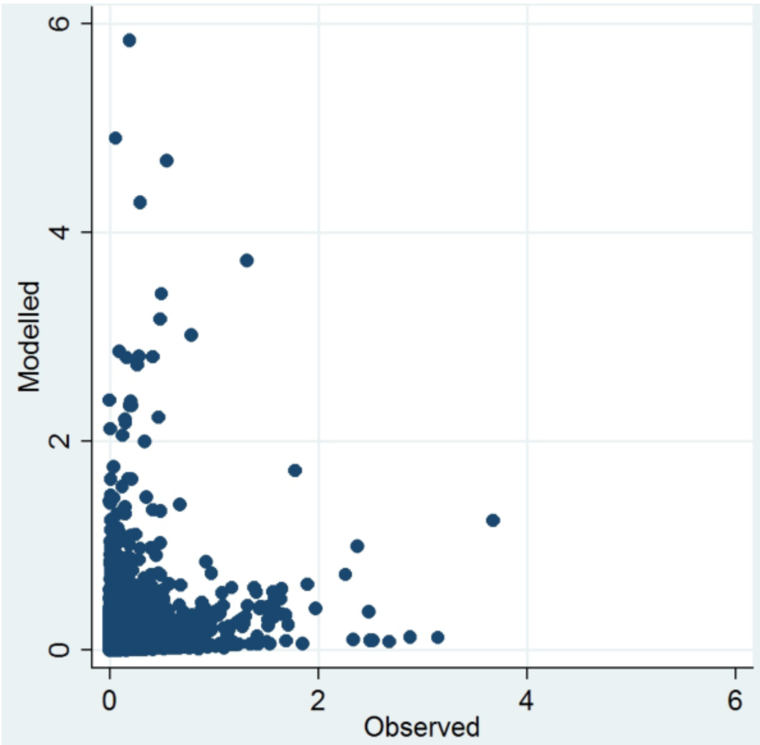
RMSWE =0.598

APPENDIX: FIGURE B5.13 NON HOME BASED CAR AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR



RMSWE =6.727

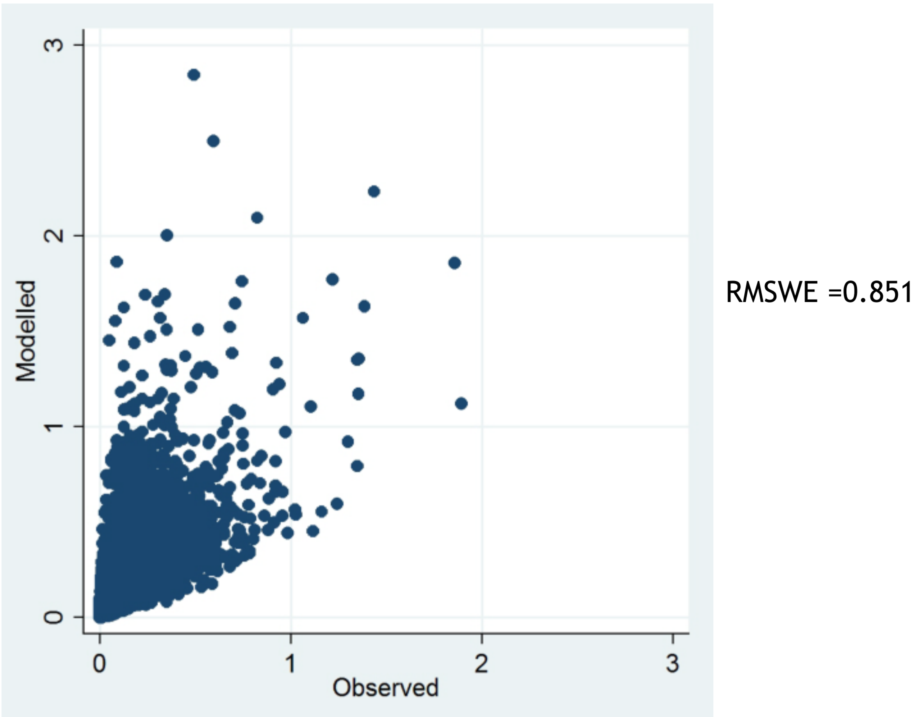
APPENDIX: FIGURE B5.14 NON HOME BASED CAR AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR



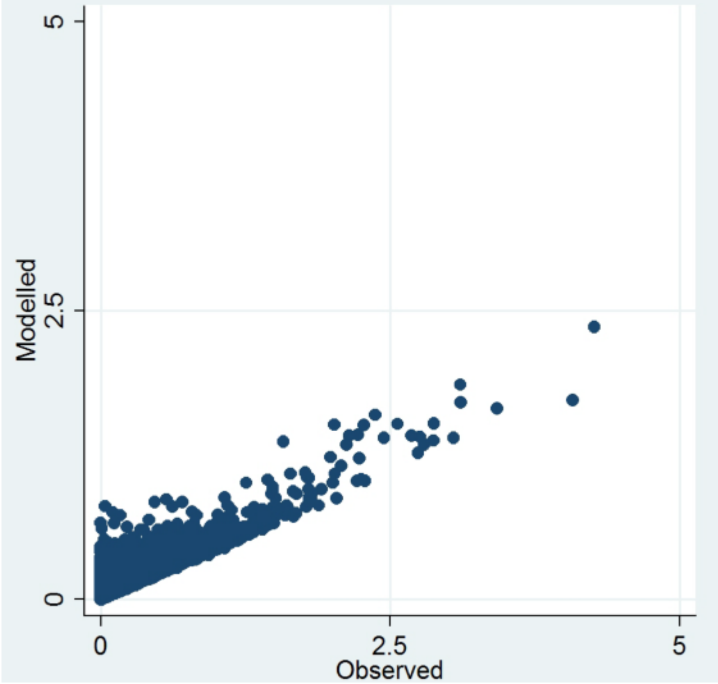
RMSWE =2.260

APPENDIX: FIGURE B5.15 NON HOME BASED CAR NON-AVAILABLE DEMAND: MODELLED V OBSERVED BY MODE

APPENDIX: FIGURE B5.16 NON HOME BASED CAR NON-AVAILABLE PT DEMAND: MODELLED V OBSERVED BY OD PAIR

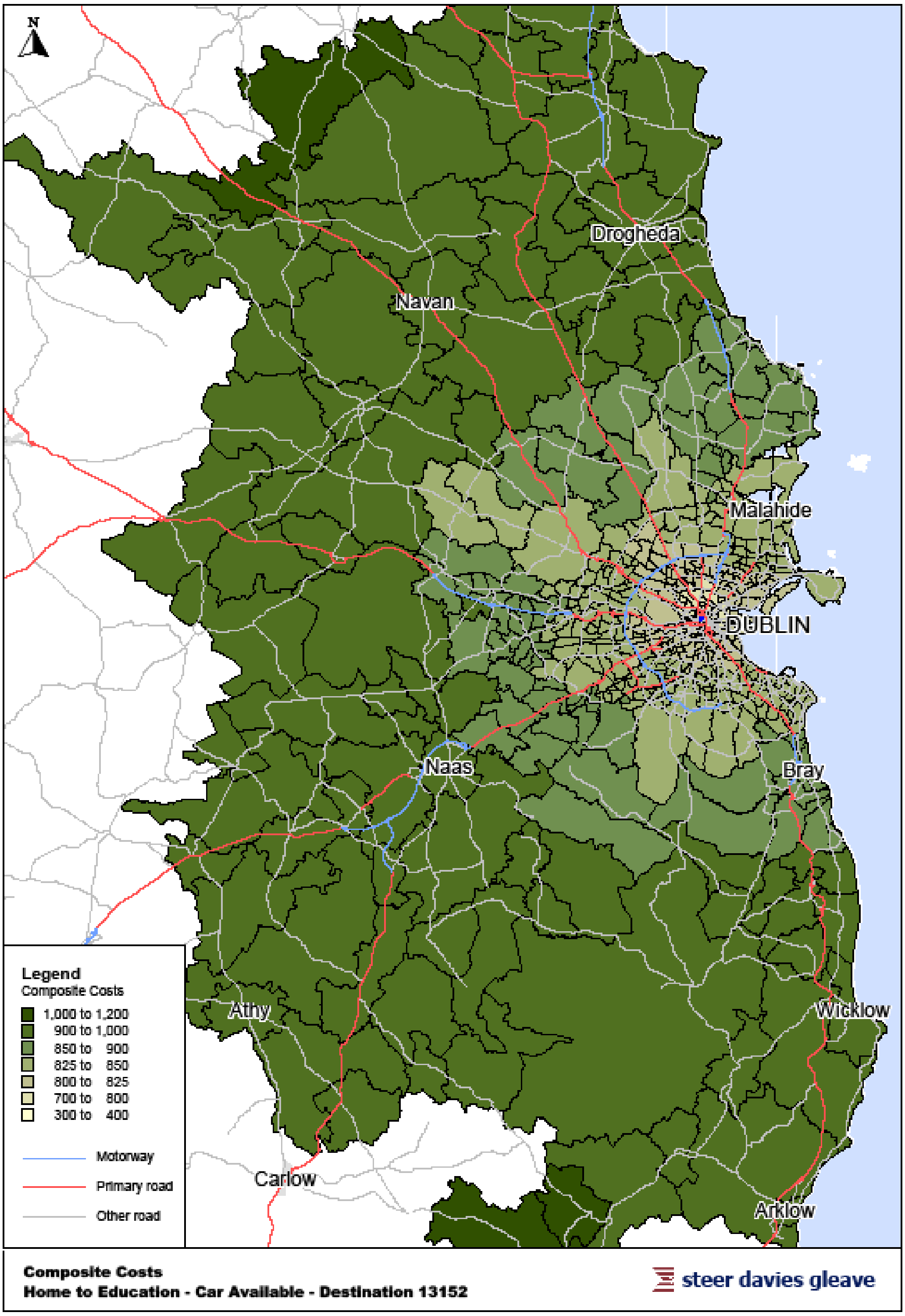


APPENDIX: FIGURE B5.17 NON HOME BASED CAR NON-AVAILABLE SLOW MODE DEMAND: MODELLED V OBSERVED BY OD PAIR

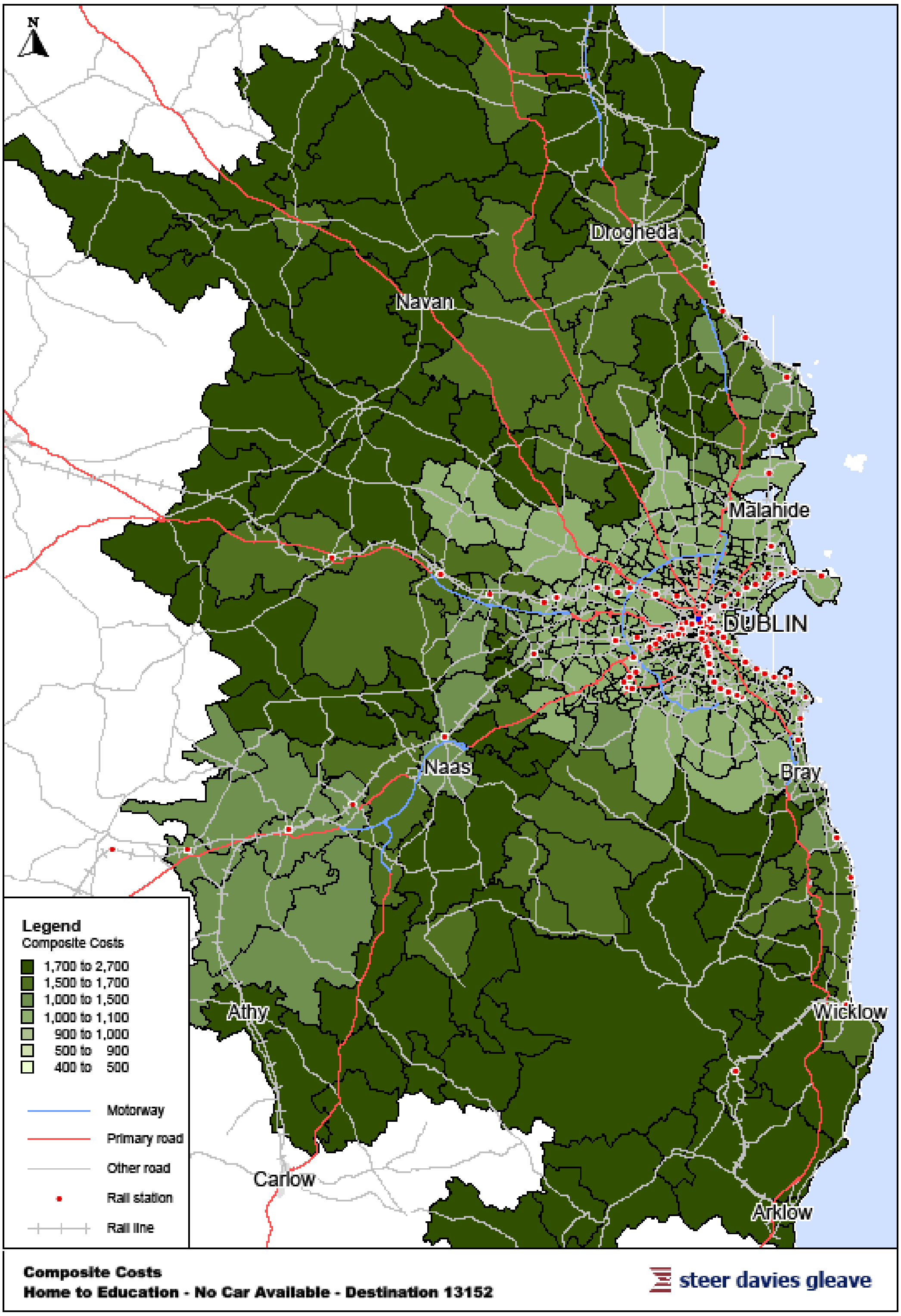


RMSWE =1.019

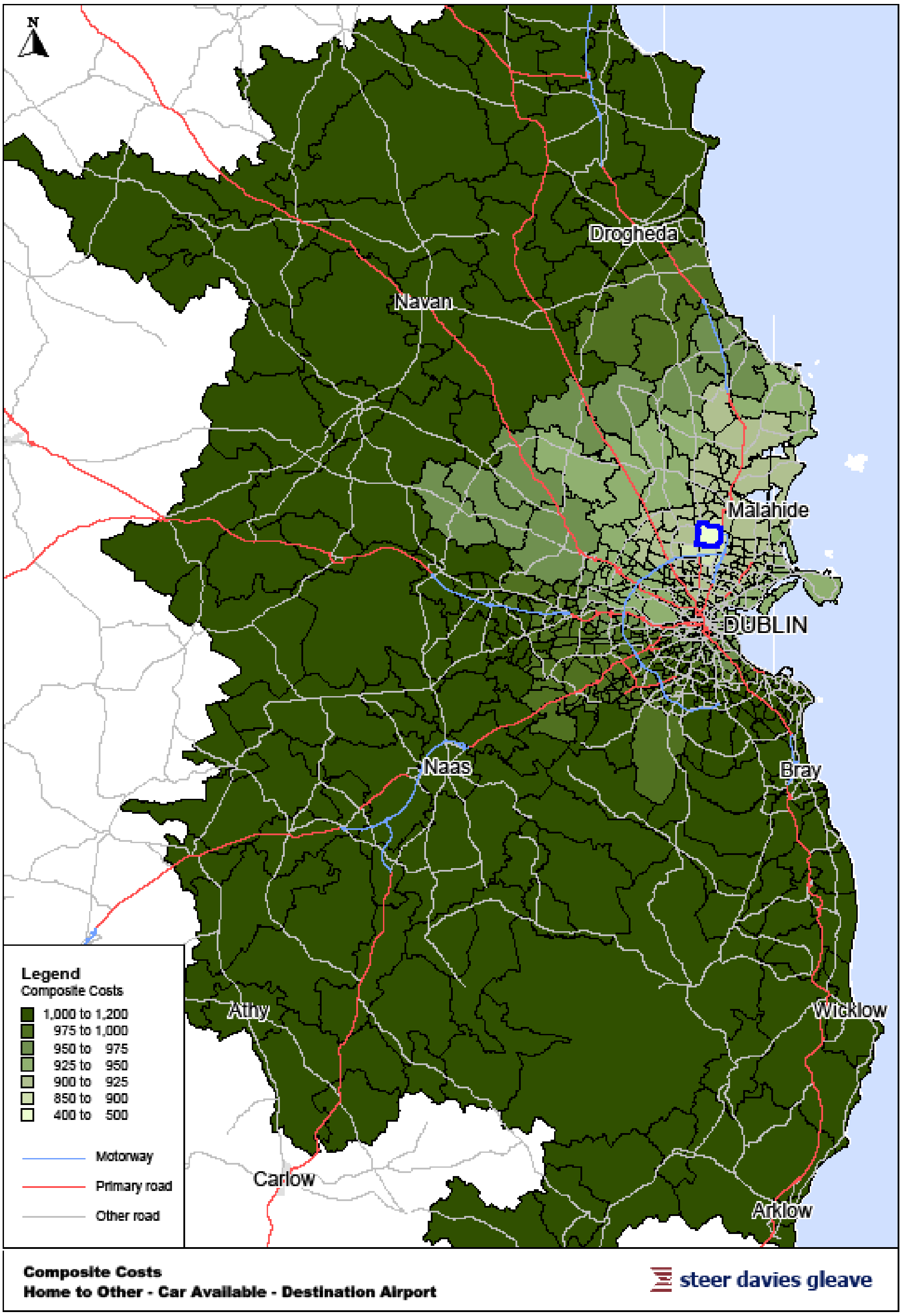
APPENDIX: FIGURE B5.18 COMPOSITE COSTS: HOME TO EDUCATION CAR AVAILABLE TRIPS (DESTINATION ZONE 13152)



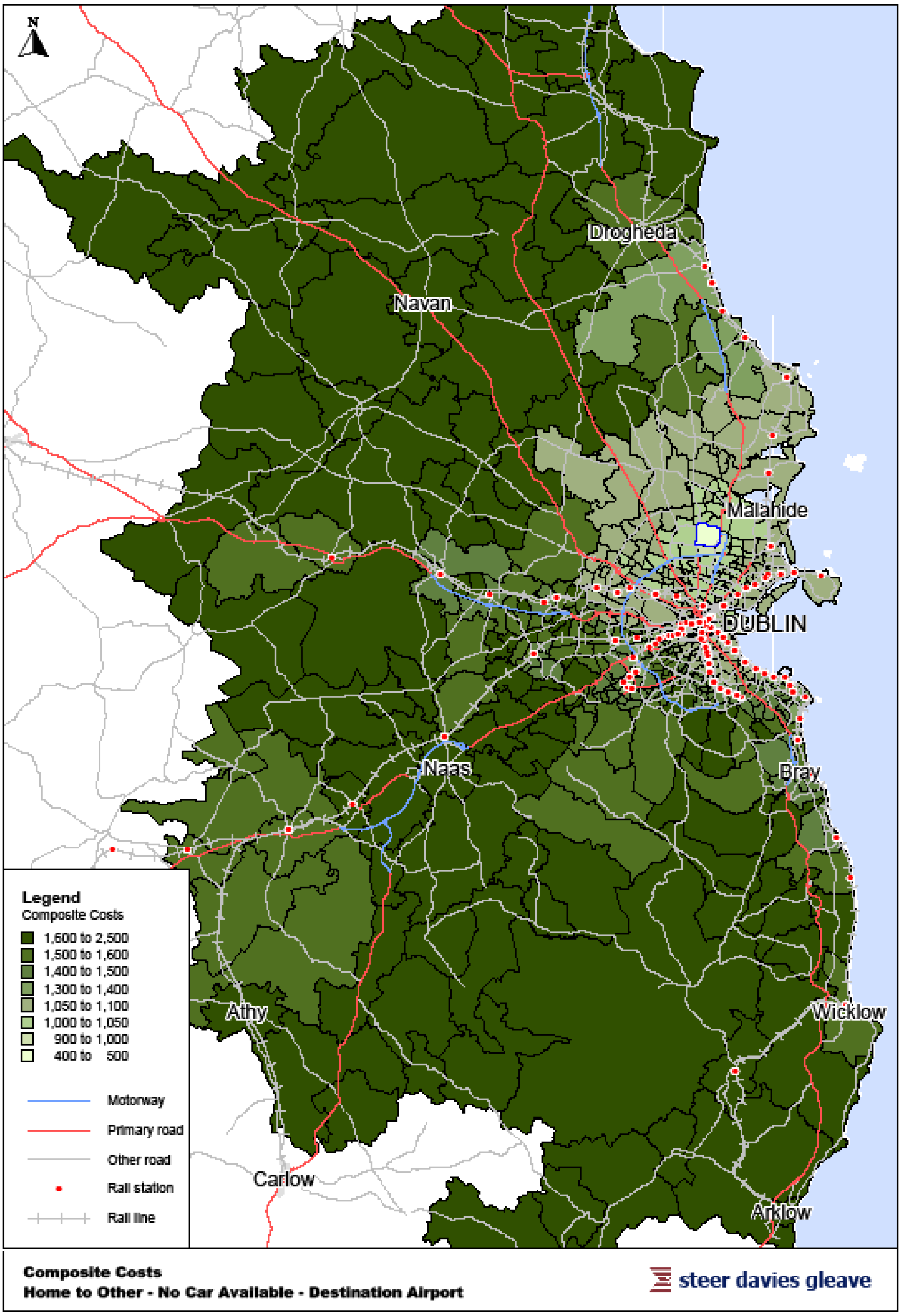
APPENDIX: FIGURE B5.19 COMPOSITE COSTS: HOME TO EDUCATION CAR NON AVAILABLE TRIPS (DESTINATION 13152)



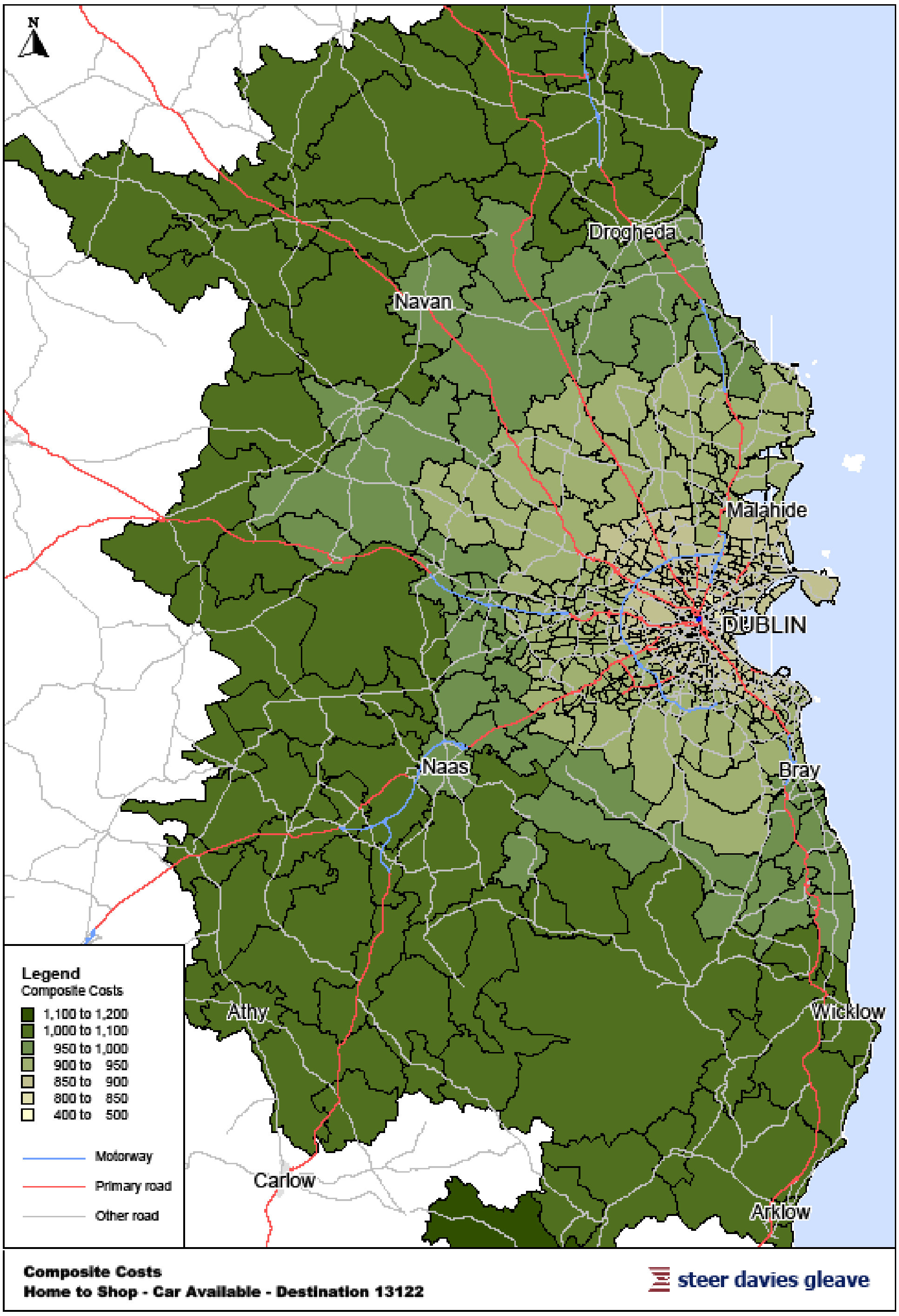
APPENDIX: FIGURE B5.20 COMPOSITE COSTS: HOME TO OTHER CAR AVAILABLE TRIPS (DESTINATION AIRPORT)



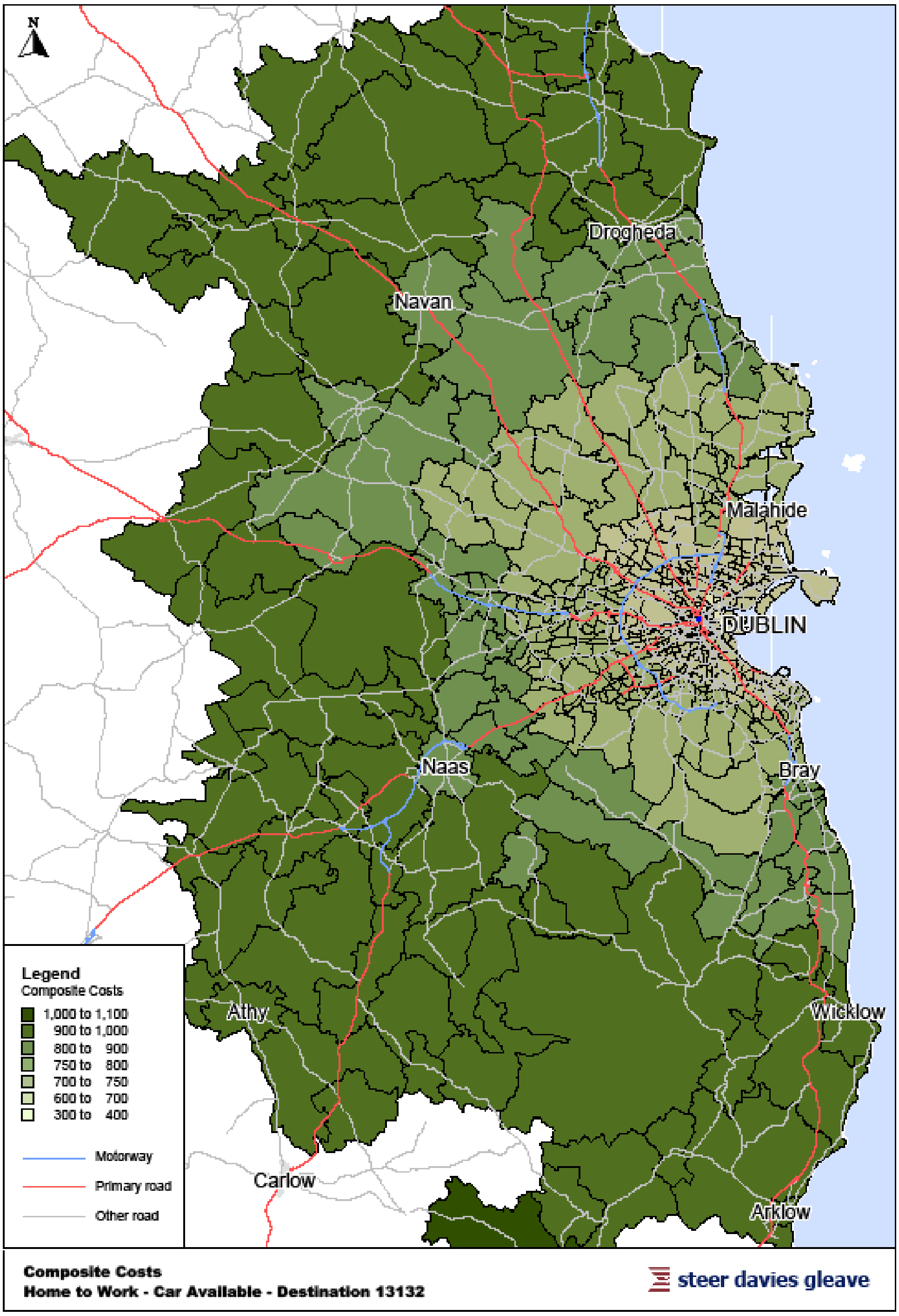
APPENDIX: FIGURE B5.21 COMPOSITE COSTS: HOME TO OTHER CAR NON AVAILABLE TRIPS (DESTINATION AIRPORT)



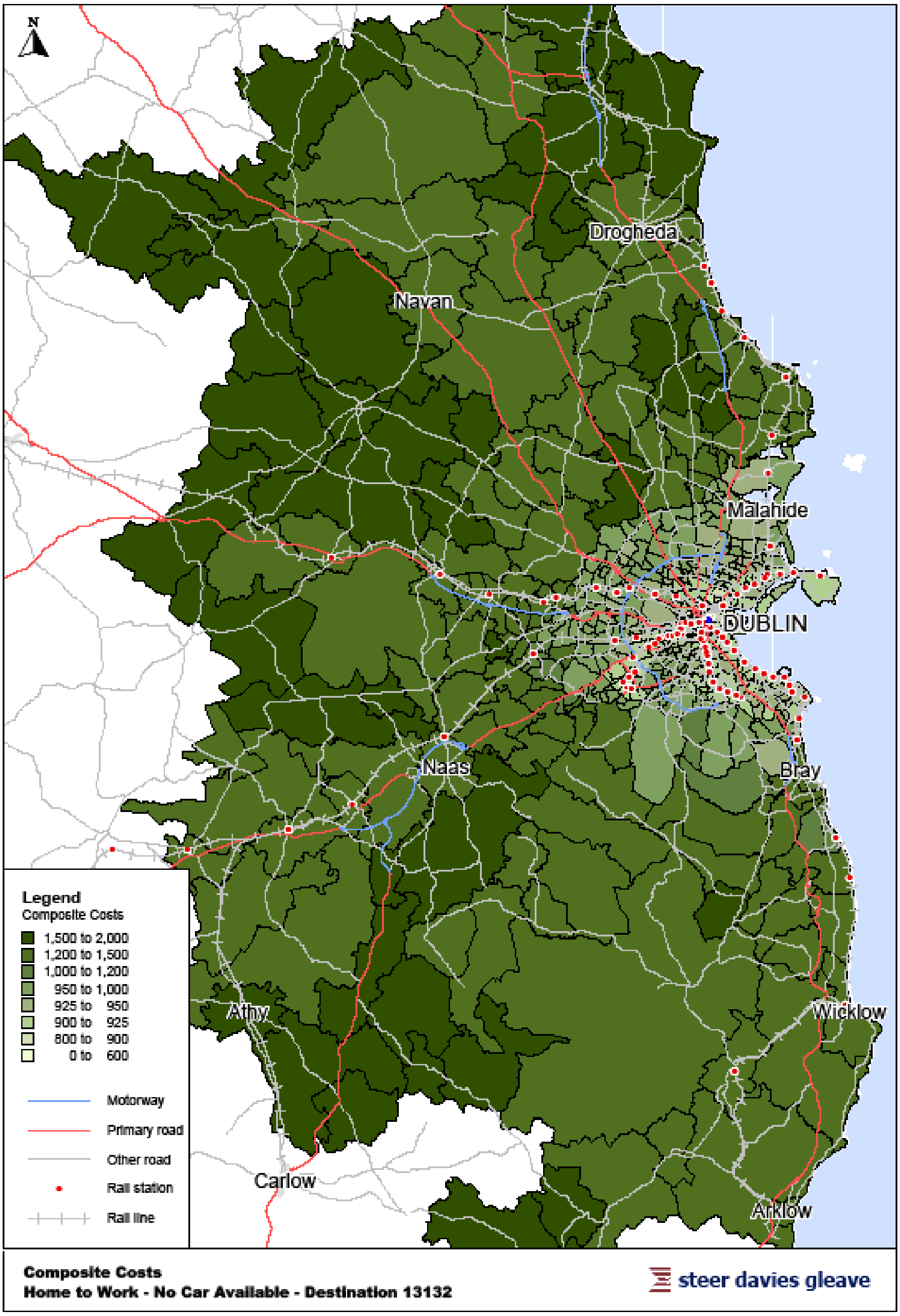
APPENDIX: FIGURE B5.22 COMPOSITE COSTS: HOME TO SHOP CAR AVAILABLE TRIPS (DESTINATION ZONE 13122)



APPENDIX: FIGURE B5.23 COMPOSITE COSTS: HOME TO WORK CAR AVAILABLE TRIPS (DESTINATION ZONE 13132)



APPENDIX: FIGURE B5.24 COMPOSITE COSTS: HOME TO WORK CAR NON AVAILABLE TRIPS (DESTINATION ZONE 13132)



CONTROL SHEET

Project/Proposal Name: DTO MODEL CALIBRATION

Document Title: Mode Choice and Time of Travel Choice

Client Contract/Project Number:

SDG Project/Proposal Number: 22044501

ISSUE HISTORY

Issue No.	Date	Details
1	March 2009	Draft Report
2	May 2009	Updates to all sections
3	June 2009	Updated following client comments
4	July 2009	Updated following client comments
5	August 2009	Final Version

REVIEW

Originator: JXS

Other Contributors: SSK

Review By: **Print:** DXC

Sign: ....

DISTRIBUTION

Clients: DTO

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