Temporal transferability of mode-destination choice models

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Declaration of contribution

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Peer reviewed papers

The following jointly authored papers have been submitted alongside this thesis:

Fox, J. and Hess, S. (2010). Review of evidence for temporal transferability of mode-destination models. Transportation Research Record 2175, 74–83.

This paper summarised material from the literature review presented in Chapter 2. My contribution as lead author was the discussion of transferability, the literature review, and the co-authored introduction and recommendations for further research sections. My co-author's contribution was to the introduction and recommendations for further research sections.

Fox, J., Hess, S., Daly, A. and Miller, E. (2014). Temporal transferability of models of mode-destination choice for the Greater Toronto and Hamilton Area. The Journal of Transport and Land Use, 7 (2), 65–86.

This paper presented a brief literature review drawing on the material presented in Chapter 2, and earlier results from the Toronto transferability analysis that is presented in its final form in Chapters 5 and 6. My contribution was as lead author for all sections of paper, and undertaking the transferability analysis that is presented. The contributions of my co-authors were through providing comments on the paper and in particular the summary section, and assistance in addressing reviewer comments. Daly and Hess also contributed through providing comments on the transferability analysis in their role as supervisors, and Miller also contributed through supply of the data and answering queries on the data.

Conference papers and presentations

The following conference papers and presentations have been undertaken during the course of the research:

Fox, J. (2011) Temporal Transferability of Mode-Destination Models: Summary of Literature, Initial Findings. European Transport Conference, Glasgow.

This paper presented a summary of the findings from the literature review presented in Chapter 2, material which is presented in greater detail in Fox and Hess (2010). The paper also presented initial results from the Toronto transferability analysis presented in Chapters 5 and 6; these results were superseded by those presented in Fox et al. (2014). Thus this paper is not enclosed.

Fox, J., Hess, S., Daly, A. and Miller, E. (2012). Temporal transferability of models of mode-destination choice for the Greater Toronto and Hamilton Area. International Conference on Travel Behaviour Research, Toronto.

This paper was later published as Fox et al. (2014) and therefore the 2012 version is not enclosed.

Daly, A., Fox, J. (2012) Forecasting model and destination choice responses to income change. International Conference on Travel Behaviour Research, Toronto.

This paper, which is enclosed, considered the issue of how to account for income growth when forecasting mode and destination choice, and informed the analysis of income growth that was discussed in Chapter 5. My contribution was to lead the sections on literature review in Section 2 and to the material on the 'welfare factor approach' presented in Section 4. My co-author's contribution was to the introduction, Section 3 on theoretical considerations, and Section 5 on summary and recommendations, as well as contributions to Sections 2 and 4.

Fox, J. (2014) Temporal transferability of mode-destination models. Applied Urban Modelling Symposium, Cambridge.

Material from Chapter 2, 5 and 6 was presented at this symposium. No paper was submitted.

Fox, J., Hess, S., Daly, A. (2015) The temporal transferability of mixed logit mode-destination choice models. International Choice Modelling Conference, Austin, Texas.

Material from Chapter 8 was presented. No paper was submitted.

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Abstract

Transport planning relies extensively on forecasts of traveller behaviour over horizons of 20 years and more. Implicit in such forecasts is the assumption that travellers tastes, as represented by the behavioral model parameters, are constant over time. This assumption is referred to as the temporal transferability of the models. This thesis presents four main contributions in this area.

First, a comprehensive review of the transferability literature in the context of the temporal transferability of mode-destination models. This review demonstrated that there is little evidence about the transferability of mode-destination models over typical forecasting horizons, and further that most evidence is from models of commuter mode choice.

Second, further empirical evidence on the temporal transferability of mode-destination models using data from Toronto and Sydney for transfer periods of up to 20 years in duration. The transferability of commuter and non-commuter travel has been compared, and models of non-commute travel were found to be less temporally transferable. Improving model specification through fixed socio-economic parameters was found to improve model transferability, and the travel time and socio-economic parameters were found to be more transferability than the cost parameters and the model constants.

Third, and most novel, what is believed to be the first empirical evidence on the impact of taking account of heterogeneity in cost and in-vehicle time sensitivity on the temporal transferability of mode-destination models. This analysis demonstrated that while accounting for taste heterogeneity led to a better fit to the base data, there was no evidence that these models were more transferable than models without random heterogeneity. This may be due to the taste heterogeneity specification over-fitting the base data.

Fourth, practical recommendations are presented for model developers on how to maximise the transferability of mode-destination models used for assessing policy.

Contents

Chapter 1

Introduction

1.1 Motivation

Local and national government agencies need to be able to forecast demand for transport, taking account of demographic changes, as well as the impact of changes to the transport infrastructure. To make these forecasts, the approach that is typically followed is to develop models that represent a tractable simplification of current behaviour, and then use those models to forecast behaviour.

The problem that is often followed it to represent the key travel choice decisions on a given day, traditionally:

- travel frequency - whether to travel, and if so how many times
- mode of travel
- destination zone
- in some cases, time at which the travel takes place

- choice of route

These choices may be modelled sequentially with no interaction of lower level choices with higher level choices, or with some representation of the impact of lower level choices, for example accessibility measures impacting on travel frequency.

While this approach could be criticised as an over-simplification of reality, it does represent a well established approach (Ortúzar and Willumsen, 2002). The focus of this research is on investigating an important component of this approach, namely the mode and destination choices, rather than investigating the validity of the wider forecasting approach.

Models to explain the mode and destination choices may be *aggregate* in nature, typically representing trips at the zonal level, or *disaggregate*, where the choices of individuals are represented at the estimation/calibration stage, and then when the models are applied the model predictions are summed over some representation of the forecast population. Explaining observed travel patterns in terms of aggregate correlations does not give a mechanism that is able to fully explain why current travel patterns have occurred, and in the context of model transferability is does not provide a theoretical basis to explain what will happen in the future as it relies on extrapolating mean effects into the future. By contrast, by explaining individual-level choices using behavioural parameters, disaggregate models are able to predict the impact of changes in transport supply and socio-economic characteristics (Ben-Akiva et al., 1976).

Separate models are usually developed by travel purpose, as experience has demonstrated that the factors influencing these choices vary according to travel purpose, for example commuter trips are attracted to zones with employment whereas primary education trips are made to zones containing primary schools. The focus of this research is on the mode and destination choice decisions, which may be modelled as sequential choices, or as a simultaneous choice. Understanding mode and destination choices is key to understanding the impacts of transport policy decisions, such as the construction of new infrastructure.

In a forecasting context, disaggregate mode-destination models are used to assess the effectiveness of different policies over forecasting horizons of 20-plus years. These models typically include detailed socio-economic segmentation, enabling both a better fit to the estimation dataset and an ability to predict the impact of trends in the behavioural variables over time, such as increasing car ownership or ageing of the population. Forecasting with such models relies on a significant assumption, namely that the parameters that describe behaviour in the base year can be used to predict future behaviour. If this assumption is violated, then the future forecasts will be subject to uncertainty, irrespective of how well the models fit in the base year, how much segmentation they incorporate, and how accurately future model inputs can be forecast.

The issue of what is meant by *transferability* is explored further in Section 2.1. For the purposes of this introduction, it is useful to cite Koppelman and Wilmot (1982), who define define a *transfer* as:

> *"...the application of a model, information, or theory about behaviour developed in one context to describe the corresponding behaviour in another context."*

This research is concerned with the transferability of particular model specifications rather than the behavioural theories underpinning those models in the context of forecasting. For example, while investigating the transferability of models which do not operate within a utility maximising framework would be an interesting area for research, the focus of this research is on models that are assumed to operate within the utility maximising framework that is discussed further in Chapter 2.

In forecasting, models developed at one point at time are applied to predict behaviour at a future point in time. It is thus assumed that the models are *temporally transferable*, i.e. that the model parameters that best explain travel behaviour at the time at which the estimation data was collected will also explain future travel behaviour.

To investigate the validity of this assumption, temporal transferability can be assessed by using datasets that have been collected at two or more points in time in the same geographical area. Provided the same variables are collected in each time point, it is possible to use the different years of data to develop identically specified models at each points in time, and make assessments of model transferability. As will be seen in Chapter 2, this is an approach that has been used by a number of other researchers to investigate the transferability of mode choice models, though evidence on simultaneous mode-destination models is extremely limited.

As transferability might be expected be to change over time, such investigations only give insight into transferability over the time horizon the data points span, but by repeating such tests using pairs of data collected over different time horizons more general assessments of temporal transferability can be made. It should be emphasised that temporal transferability is not stated here as the only condition that must be satisfied to produce accurate forecasts, rather it is a factor that is is often overlooked, whereas significant effort may go into predicting the composition of the future population and other model inputs, and sensitivity tests are often run to assess the impact of uncertainty in key model inputs.

The issue of transferability received some attention in the late 1970s and early 1980s when disaggregate mode choice models were being applied for the first time, but then seems to have largely dropped off the research agenda. Recent efforts to develop activity based models, particularly in the US, have sparked renewed interest in the topic of transferability. This thesis revisits the issue in the context of mode-destination models applied over forecasting horizons of 20 years of more.

Over forecasting horizons of this period, destination choice changes would be expected in response to policy, and for this reason evidence from models of mode choice alone is not sufficient.

1.2 Objectives

This research has the following objectives:

- to assess the transferability of mode-destination choice models over long-term forecasting horizons, i.e. up to 20 years;
- to investigate how model transferability evolves over time;
- to investigate the transferability of mode-destination choice models incorporating taste heterogeneity; and
- to advise how best to specify models to maximise their temporal transferability.

A more detailed set of aims are presented at the end of Chapter 2, following review of the temporal transferability literature.

1.3 Contribution

Four key contributions to transferability research are presented in this thesis.

1. a comprehensive review of the transferability literature in the context of the temporal transferability of mode-destination models;
2. further empirical evidence on the temporal transferability of mode-destination models using data from Toronto and Sydney for transfer periods

of up to 20 years in duration, including a cross city comparison of model transferability;

3. most novel, what is believed to be the first empirical evidence on the impact of taking account of heterogeneity in cost and in-vehicle time sensitivity on the temporal transferability of mode-destination models; and

4. practical recommendations for model developers on how to maximise the transferability of mode-destination models used for assessing policy.

1.4 Thesis layout

Chapter 2 presents a review of the model transferability literature, starting with discussions of what is meant by model transferability, and the distinction between temporal and spatial transferability. The Chapter then discusses how transferability can be assessed, before going on to review the temporal transferability and spatial transferability literature. It concludes with by summarising the key findings from the temporal transferability literature and then sets out specific research aims for the empirical work.

Chapter 3 discusses the datasets that have been assembled to make empirical tests of model transferability. The chapter begins with a discussion of the different datasets considered for analysis, before presenting details for the two datasets that have been used for analysis, specifically datasets from Toronto, Canada and Sydney, Australia.

Chapter 4 documents the model development effort. It starts by outlining the software used for the estimation and analysis work, before going on to document the mode and destination alternatives, the model specifications, the utility functions used in the models, and the key model results.

Chapter 5 presents analysis of parameter transferability using both the Toronto and Sydney datasets. It starts by considering the issue of how to adjust cost sensitivity to take account of real growth in incomes over time, and then summarises how the comparison of individual parameters has taken account of differences in scale between different years of data. With these two considerations taken into account the chapter goes on to present analysis testing whether the changes in individual parameters are significantly different over time, and analysis of the relative changes in parameter magnitude over time. Changes in the cost and time parameters are a particular focus as these parameters are key for testing policy.

Chapter 6 presents analysis of model transferability using both the Toronto and Sydney datasets. The first two sections use statistical tests of transferability, and include investigation of how transferability changes over time and as the model specification is improved. The later sections focus on more pragmatic tests, with analysis of how well the models are able to predict observed changes in mode share and trip length over time, and of changes in the elasticities of the models in response to changes in travel cost and travel time.

Chapter 7 presents analysis of partial transfer and pooled models using the Toronto dataset. The partial transfer analysis investigates how mode scale evolves over time for different groups of utility parameters. The pooled analysis investigates whether if datasets from different years can be best combined to enhance model transferability relative to using data from the most recent year only, and if so how best to combine them.

Chapter 8 presents analysis that investigates the impact of introducing random taste heterogeneity for cost and in-vehicle time sensitivities on the transferability of the Toronto mode-destination models.

Finally, Chapter 9 presents conclusions and suggests directions for future research.

Chapter 2

Literature review

This chapter starts with by setting out the discrete choice framework used to develop mode-destination choice models, and with a review of the literature on mode-destination choice models. This review is presented prior to before introducing the key concept of model transferability in Section 2.2 because the various sections on transferability are most logically presented sequentially.

Once the mode-destination choice model literature has been discussed, Section 2.2 goes on to discuss what is meant by model transferability, and in particular explains how the concept of temporal transferability relates to this particular research.

Section 2.3 summarises the measures that have been used to assess model transferability in the literature, and sets out the set of measures used to assess transferability in this research.

Section 2.4 presents a review of the literature on temporal transferability, the literature most relevant to this research.

Section 2.5 covers the literature on spatial transferability. Although findings on spatial transferability are less relevant to the objectives of this research, the methodologies that have been developed to undertake model transfers came from the spatial transferability literature. Furthermore, most of the key early papers on the transferability of disaggregate models were concerned with spatial transfer.

Finally, Section 2.6 with a summary of the findings from the transferability literature, and drawing on the literature review sets out more specific research aims for the empirical research.

Material from this literature review was presented in Fox and Hess (2010)[1] and in Fox et al. (2014).

2.1 Disaggregate mode-destination choice models

2.1.1 Discrete choice model framework

This section sets out how disaggregate models of mode-destination choice that are the focus of this research are defined within the discrete choice modelling framework. Later, section 2.1.3 discusses some other model forms, such as the cross-nested logit model, that can be used to model mode and destination choices.

Discrete choice models represent the choice of a decision maker between a number of discrete alternatives. Depending on the choice that is being represented, the decision maker might be an individual, a household, a company or any other decision making unit. To model mode-destination choice, most models have represented the choice at the *individual* level, as this is judged to be the level at which the travel decision is made. However, in some studies models have been

[1] Winner of the 2010 Fred Burggraf Award for Planning and Environment.

estimated at the household level, for example the early work to develop shopping mode-destination models of Ben-Akiva (1974). The transferability analysis presented in this thesis has been undertaking using samples of home–work and home–other travel trips, and to model these purposes it has been assumed that the individual rather than the household is the decision making unit.

Train (2003) sets out the three characteristics that the set of alternatives, the *choice set*, needs to satisfy to fit within the discrete choice framework. First, the alternatives must be *mutually exclusive*. Second, the alternatives must be *exhaustive*, i.e. cover all possible alternatives. Third, the number of alternatives must be *finite*.

In the context of simultaneous models of mode-destination choice, alternatives are specified to define the possible combinations of modal alternatives and destination alternatives. The exclusivity condition is satisfied by categorising the modes into a number of mutually exclusive modal alternatives, and by breaking up the study area into a number of contiguous non-overlapping model zones[2]. As the numbers of modal and destination alternatives are finite, the total number of alternatives represented is also finite. However, the requirement that the choice set be exhaustive is often not strictly met. Infrequently chosen modes such as motorcycle may be excluded from the choice set because the low number of observations does not justify the additional complexity of modelling them with a separate alternative. Furthermore, destination alternatives outside the study area are not always represented on the basis that they are rarely chosen.

Typically decisions to restrict the choice set in this way are justified by undertaking analysis to demonstrate that the excluded alternatives represent a small fraction of the observed choices. In the Toronto transferability analysis, between 3.4% and 5.9% of the data for a given year has been excluded because the mode

[2]In some model areas one or more zones may be used to represent an island that is separated from the main model area by a body of water, in these cases the island zones may not be contiguous with the rest of the model zones.

is rarely chosen and complex to model, or because the mode chosen was not recorded in all of the other years of the TTS data[3].

Restricting the choice set to more frequently chosen alternatives can be justified on theoretical grounds as well. As discussed in Ben-Akiva and Lerman (1985), for a multinomial model the estimation can take advantage of the independence from irrelevant alternatives (IIA) property, which allows consistent estimates of the model parameters from a sub-set of the alternatives.

The key assumption used to explain choices within the discrete choice model framework is that of *utility maximisation*: individuals are assumed to select the alternative that maximises their utility (Marschak, 1960). If individuals are labeled n, each alternative in the choice set can be referenced as $j = 1, ..., J$, and the utility individual n obtains from alternative j is U_{nj}, then the model framework is that the individual will choose alternative i only if $U_{ni} > U_{nj} \forall j \neq i$.

Making the assumption of utility maximisation, which implies that individuals are rational in that they select the alternative that maximises their utility, allows discrete choice models to be specified within an economic framework.

If it was possible to fully observe individual utilities, then the mode-destination models would be *deterministic*, as they could predict exactly which alternative each individual would choose. However, in practice analysts cannot fully observe individual utilities, and so utility is decomposed into *deterministic utility* V_{nj} and *random utility* ε_{nj}:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{2.1}$$

The deterministic utility component is defined as a function of measurable attributes of each mode-destination alternative, x_{nj}, and a vector of model pa-

[3]This second condition is only required because transferability analysis is being undertaken and therefore the modal alternatives must be the same for all the years of data.

rameters which define the tastes of individual n, β_n. While it is possible to use non-linear functions for the parameters, such as the Box-Cox formulation (Box and Cox, 1964), in the multinomial and nested logit formulations it is assumed that the function is linear in parameters. This allows us to write:

$$U_{nj} = \beta_n x_{nj} + \varepsilon_{nj} \tag{2.2}$$

An important point to note is that because the analyst does not know $\varepsilon_{nj} \forall j$ these terms are treated as random. The presence of the random term means that the choice process becomes *probabilistic*, and the model is termed a *random utility model (RUM)* (Marschak, 1960). The probability that individual n chooses alternative i can now be written:

$$P_{ni} = P(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \; \forall j \neq i) \tag{2.3}$$

Different assumptions about the distribution of ε_{nj} give rise to different model types. Logit models have been used for the transferability analysis presented in later chapters.

Multinomial logit

Despite the availability of more advanced model forms, the multinomial logit model (MNL) remains widely used in transport planning, as it has a closed form expression that is easy to estimate. The logit formula was originally derived by Luce (1959), and later McFadden (1974) showed that the logit formula for the choice probabilities implies that the unobserved utility is distributed extreme value.

The logit model assumes that each random error term ε_{nj} is independently, identically distributed extreme value. This distribution is also called Gumbel and type I extreme value, and is close to the normal distribution but with slightly fatter tails. Given the Gumbel distribution for ε_{nj}, Train (2003) sets out the algebra that shows the MNL choice probabilities can be written:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} \tag{2.4}$$

Daly (1982) discusses the estimation of logit models incorporating *size variables*. Size variables S represent the *quantity* of elementary choices in each destination alternative, and appear in the models in a different way from other variables x that describe the *quality* of the different alternatives. Specifically, size variables are formulated so that the probability of choice is proportional to the size variable. This is achieved by entering the size variables into the utility functions in logarithmic form:

$$P_{d'} = \frac{e^{(V_{d'} + \alpha ln S_d)}}{\sum_{d=1}^{D} e^{(V_d + \alpha ln S_d)}} = \frac{S_d^{\alpha} e^{V_{d'}}}{\sum_{d=1}^{D} S_d^{\alpha} e^{V_d}} \tag{2.5}$$

where α is the size parameter, which in most practical applications is constrained to one so that the model is independent of the zone system used for estimation.

In the context of simultaneous mode-destination choice, we are predicting the choice of mode-destination alternative $m'd'$ from modal alternatives $m = 1, ..., M$ and destination alternatives $d = 1, ..., D$. Noting that the size parameter α has been constrained to one, the probability expression can be written:

$$P_{m'd'} = \frac{S_{d'} e^{V_{m'd'}}}{\sum_{m=1}^{M} \sum_{d=1}^{D} S_d e^{V_{md}}} \tag{2.6}$$

The key assumption in the MNL model is that the ε_{nj} terms are independent. This means that the unobserved component of utility for a given alternative is unrelated to the unobserved component of utility for another alternative. This has an important implication for the substitution patterns in the model. In an MNL model, if an alternative is improved it draws demand proportionately from the other alternatives. So, if an improvement to one alternative caused demand for another alternative to reduce by 5%, then the same 5% reduction in demand is observed for all alternatives apart from the improved alternative. This property is termed *Independence from Irrelevant Alternatives (IIA)*.

Nested logit

For modelling mode-destination choice, there are a number of ways in which the IIA property may be violated. It may be that in response to an improvement to a given mode-destination alternative, demand is more likely to be drawn from other modes travelling to the same destination than from other destinations. Conversely, it may be that demand is more likely to be drawn from other destinations reached by the same mode than from other modes. Finally, it may be that some modal alternatives are closer substitutes than others, for example that individuals are more likely to switch between different PT modes than between PT and non-PT modes. Nested logit models are able to take account of these more complex substitution patterns by accounting for correlation between the ε_{nj} terms across different alternatives.

In the nested logit model, alternatives are grouped into nests. Alternatives that are expected to be closer substitutes are placed in the same nest, and the error terms ε_{nj} for all alternatives in the same nest are correlated. However, there is no correlation between the ε_{nj} terms for two alternatives in different nests. For two alternatives within the same nest, the ratio of probabilities is independent of all other alternatives, so the IIA property holds within each nest. However, for two alternatives in different nests, the ratio of probabilities can depend on the other alternatives, so that in general IIA does not hold for alternatives in different nests.

Using the notation given in Train (2003), the set of alternatives j can be partitioned into K non-overlapping nests $B_1, B_2, ..., B_K$. Williams (1977), Daly and

Zachary (1978) and McFadden (1978) independently proved that the nested logit model is consistent with utility maximisation, and that the choice probability for alternative i in nest B_k can be written:

$$P_{ni} = \frac{e^{V_{ni}/\lambda_k}(\sum_{j\in B_k} e^{V_{nj}/\lambda_k})^{\lambda_k-1}}{\sum_{l=1}^{K}(\sum_{j\in B_l} e^{V_{nj}/\lambda_l})^{\lambda_l}} \tag{2.7}$$

Values for λ_k between zero and one ensure consistency with utility maximising behaviour. Train (2003) notes that with values of λ_k greater than one the model is consistent with utility maximising behaviour for a range of the explanatory variables, but not for all values. It can be seen that if $\lambda_k = 1$ for all k, then the term in brackets on the numerator of Equation 2.7 is one, and the probability formula reduces to the MNL formula given in Equation 2.4. Values for λ_k closer to zero indicate the alternatives within nest k are much closer substitutes (i.e. more correlated) than alternatives in other nests.

The expression in Equation 2.7 is not particularly tractable to work with. However, Train (2003) illustrates how this equation can be simplified by decomposing observed utility into two components:

$$U_{nj} = W_{nk} + Y_{nj} + \varepsilon_{nj} \tag{2.8}$$

for $j \in B_k$ where:

W_{nk} depends only on variables that describe nest k
Y_{nj} depends on variables that describe alternative j, and which vary over the alternatives within nest k

Using Bayes rule, we can write:

$$P_{ni} = P_{nB_k} P_{ni|B_k} \tag{2.9}$$

$$P_{nB_k} = \frac{e^{W_{nk}+\lambda_k I_{nk}}}{\sum_{l=1}^{K} e^{W_{nl}+\lambda_l I_{nl}}} \tag{2.10}$$

$$P_{ni|B_k} = \frac{e^{Y_{ni}/\lambda_k}}{\sum_{j \in B_k} e^{Y_{nj}/\lambda_k}} \tag{2.11}$$

$$I_{nk} = ln \sum_{j \in B_k} e^{Y_{nj}/\lambda_k} \tag{2.12}$$

The I_{nk} term is called the *inclusive value* or *logsum*, and brings information from the lower model into the upper model.

It should be emphasised that the nested logit model structure does not imply sequential choice behaviour, rather a simultaneous choice between the different alternatives is represented taking account of correlation between the different alternatives.

An important issue highlighted by Koppelman and Wen (1998) is that there are two different formulations of the nested logit model in use. The version presented in Equations 2.10 to 2.12 is the RU2 formulation or Utility Maximising Nested Logit Model (UMNL) formulation. In the alternative formulation, referred to as the RU1 or Non-Normalised Nested Logit (NNNL), the coefficients in the lower model are not divided by λ_k in Equation 2.11[4]. Koppelman and Wen stated that

[4]The RU1 and RU2 notation was coined by Hensher (2002) and has been used in the discussion in the remainder of this section.

the RU1 model is not consistent with utility maximisation when coefficients are common across nests.

However, Daly (2001) notes that the RU1 and RU2 formulations are equivalent when the trees are symmetrical, that is to say all of the structural parameters at each level are equal, and so if this condition is satisfied models specified using the RU1 form with parameters shared across nests are consistent with utility maximisation. In this work, the ALOGIT estimation software has been used because it is quicker than alternative estimation software for estimating mode-destination choice models, and ALOGIT works with the RU1 formulation. All of the tree structures that have been estimated are symmetrical, and according to Daly (2001) are therefore consistent with utility maximisation.

Daly (2001) also highlights other conditions under which the RU1 and RU2 formulations are equivalent, specifically if there are no generic coefficients multiplying terms in the utility functions in different nests, or where alternatives with asymmetric branching have zero utility. Neither of these conditions hold in the models tested in this research; as the tree structures are always symmetrical consistency between RU1 and RU2 is always achieved.

Two alternative (symmetrical) tree structures for mode and destination choice have been tested in this research, a modes above destinations structure, and a destinations above modes structure. These structures investigate the relative levels of error in the two choices in order to arrive at a structure where the choice with the lower level of error is represented beneath the choice with a higher level of error. The lowest level choice is more sensitive to changes in utility, as the structural parameters have the effect of reducing the scale of utility at higher levels in the tree to compensate for the higher levels of error. It is important to emphasise therefore that the mode-destination tree structure is a reflection of the error structure in a model of simultaneous mode and destination choice, it is not a reflection of the sequence in which the mode and destination choices are made.

The choice probability calculations for these two structures are detailed in the following sections. Chapter 4 discusses the results of tests of the two alternative structures for the Toronto and Sydney models.

Destinations above modes structure

Noting that the models are estimated using the RU1 formulation, dropping the index for individual n for clarity, noting that the size parameter α has been constrained to one and that the size functions must enter at the destination level in the structure for the proportionality condition to hold, the choice probabilities from Equations 2.9 to 2.12 can be written:

$$P_{m'd'} = P_{d'} P_{m'|d'} \tag{2.13}$$

$$P_{d'} = \frac{S_{d'} e^{(\theta_{dm} ln \sum_{m=1}^{M} e^{V_{md'}})}}{\sum_{d=1}^{D} S_d e^{(\theta_{dm} ln \sum_{m=1}^{M} e^{V_{md}})}} \tag{2.14}$$

$$P_{m'|d'} = \frac{e^{V_{m'd'}}}{\sum_{m=1}^{M} e^{V_{md'}}} \tag{2.15}$$

where θ_{dm} is the structural parameter that governs the relative sensitivity of destination and mode choices. To *guarantee* consistency with RUM θ_{dm} must lie between zero and one, though Börsch-Supan (1990) demonstrated that under certain conditions it is possible to estimate models where the structural parameter is greater than one that are consistent with RUM.

Modes above destinations

In the modes above destinations structure, all of the utility functions including the size functions are specified at the lower level of the structure. Again noting that the models are estimated using the RU1 formulation, dropping the index for individual n for clarity, and noting that the size parameter α has been constrained to one, the choice probabilities from Equations 2.9 to 2.12 can be written:

$$P_{m*d*} = P_{m*}P_{d*|m*} \tag{2.16}$$

$$P_{m*} = \frac{e^{(\theta_{md} ln \sum_{d=1}^{D} e^{V_{m*d}})}}{\sum_{m=1}^{M} e^{(\theta_{md} ln \sum_{d=1}^{D} e^{V_{md}})}} \tag{2.17}$$

$$P_{d*|m*} = \frac{S_{d*}e^{V_{m*d*}}}{\sum_{d=1}^{D} S_d e^{V_{m*d}}} \tag{2.18}$$

where θ_{md} is the structural parameter that governs the relative sensitivity of mode and destination choices. To guarantee consistency with RUM θ_{md} must lie between zero and one.

2.1.2 The development of mode and destination choice models

Predicting the modes future travellers will choose, and the destinations they will travel to, is fundamental to making forecasts of travel demand. In the traditional aggregate four-stage model, distribution and mode choice are predicted as separate choices. Demand is allocated over destinations first, and then the mode split step is applied for each origin-destination pair (Ortúzar and Willumsen, 2002). The models are aggregate in the sense that the dependent variable represents a group of observations, namely observed data grouped to model zones.

Disaggregate models of simultaneous mode-destination choice are disaggregate in the sense that they are estimated from observations from individual decision makers, though it should be emphasised that the models are not individual-level models, rather individual-level data is used to estimate models that represent average preference for a particular segment of the population. Kitamura et al. (1998) highlight that while models is this type are disaggregate in their treatment of travellers, they are aggregate in their treatment of destination opportunities which are represented at the zonal level.

Nearly all of the disaggregate models of simultaneous mode-destination choice that have been developed since the 1970s have used either multinomial or nested logit models. Vovsha (1997) suggests this is because these models are theoretically sound, they have a simple analytical structure that is readily understood, and software to calibrate these models is widely available. Nested model forms have been used to develop model structures where modes are grouped below destinations, or destinations are grouped below modes, to investigate the relative sensitivity of these two choices. Furthermore, nested structures may be used to group more similar modes together, the most usual example being grouping public transport (PT) modes together to reflect the higher rates of substitution between PT modes than between PT and non-PT modes. For example, Fox et al. (2011) document the development of simultaneous models of mode-destination choice for Sydney that have main mode choice as the highest level (least sensitive) choice, with the choice between different public transport modes as the middle level choice, and then destination choice as the lower level choice.

This section goes to to discuss the early literature that set out the arguments for modelling mode and destination choice simultaneously before going on to describe both pioneering and more recent applications of mode-destination choice models.

Simultaneous models of mode and destination choice

Estimating the mode and choice decisions simultaneously allows the relative sensitivity of the two choices to be identified from the estimation data, rather than imposing a sequence to the choices *a priori*, and from a behavioural perspective is more realistic, for example by properly representing the choice between walking to the corner shop or driving to a more distant supermarket. As noted below, some of the early work in developing simultaneous models noted that key parameter estimates may be significantly different in simultaneous models.

Richards (1974) outlined the arguments for moving from modelling travel choices as a series of sequential and partially independent decisions, such as separate models for mode and destination choices, towards simultaneous choice models. He suggested that a truly behavioural model should ideally include all those choices relevant to the period for which predictions are required and which can be expected to significantly influence those predictions. Estimating simultaneous models for mode and destination choice was identified as a substantial improvement on the sequential modelling approach that was possible with the data and modelling techniques available at that time.

In the same issue of Transportation, Richards and Ben-Akiva (1974) presented results for a simultaneous destination and mode choice model for shopping travel estimated using data from the Eindhoven region in The Netherlands. Richards and Ben-Akiva do not explicitly test whether the simultaneous models that they develop gave better predictions than separate mode and destination choice models. However, in their introduction they note that because mode and destination choices are expected to be inter-dependent a simultaneous model is preferred to sequential models. Results are presented in the paper for both mode-choice only and mode-destination choice models. A comparison of the two sets of parameters demonstrates that the mode-destination choice specification yields more significant parameter estimates. For example, the in-vehicle time parameter has a t-ratio of 13.3 in the mode-destination specification compared to just 3.6 in the mode-choice only specification, which in the author's view is likely to be due to the greater inter-alternative variation in travel times in the simultaneous model specification.

Ben-Akiva (1974) discussed some of the practical advantages of using disaggregate models in place of the aggregate models widely used at the time. As aggregate models lose detailed information when data is aggregated to model zones, Ben-Akiva suggested that it should be possible to develop disaggregate models using smaller sample sizes. Furthermore, because disaggregate models seek to explain the observed choices using behavioural model parameters, Ben-Akiva suggested that the models should be more transferable to other areas.

Ben-Akiva developed a simultaneous model of mode and destination choice for shopping tours recorded in a 1968 home interview survey in metropolitan Washington D.C.. The models were developed at the household level, as that was judged to be the decision making unit for shopping travel. He compared the results from the simultaneous models to those from the two possible sequential model structures, predicting destination choice first and then predicting mode choice conditional on destination $(m|d)$, and predicting mode choice first and then predicting destination choice conditional on mode choice $(d|m)$. In terms of overall fit to the data, there was little difference between the three different approaches. However, there were significant differences in the implied values of time (VOT), with the VOTs in the simultaneous model higher than those in the $(m|d)$ model, but lower than those in the $(d|m)$ model. Furthermore, the cost elasticities in the simultaneous model where much lower than those in the $(m|d)$ model. Thus while the paper does not demonstrate that the simultaneous model is superior to sequential models, it does illustrate that the choice of model structure has an important impact on the response characteristics of the models.

In Adler and Ben-Akiva (1975), the shopping mode-destination choice structure developed by Ben-Akiva was extended to include frequency choice, with the choice between zero and one household shopping tours represented. The authors asserted that Ben-Akiva's finding that the model results are sensitive to the choice structure used to represent mode and destination choices makes a convincing case for the use of a joint-choice structure. This is only true if the model results from the simultaneous structure were demonstrated to be more plausible, and the Ben-Akiva paper presented no such evidence. The frequency choice introduced to the model structure by Adler was a binary choice between no tour and one return shopping tour (home-shopping-home). The plausibility of the joint model structure was tested by making five policy tests to represent include gas and parking cost increases, incentives to encourage car pooling, and wider availability of transit. The joint model responded plausibly to these policy tests.

In summary, a number of these early papers claim that mode and destination choices should be modelled simultaneously rather than sequentially to better reflect how individuals make choices, which is plausible from a behavioural perspective. However, the evidence from these studies that the simultaneous approach actually results in better quality models and forecasts is limited.

Pioneering applications of mode-destination models

Ben-Akiva et al. (1976) provided an overview of research into disaggregate models at that time, and summarised some practical applications. They noted that the initial applications of disaggregate models from 1962 onwards were all for the choice of travel mode, the first extension to a multi-dimensional choice situation was a 1972 study by Charles River Associates that developed models for frequency, destination and mode choice. However, each choice was modelled separately in a sequential fashion. Thus the first simultaneous mode-destination choice model appears to be the Eindhoven models described in Richards and Ben-Akiva (1974).

Hoorn and Vogelaar (1978) describes the development of the SIGMO model system for Amsterdam, one of the first disaggregate model systems. In the SIGMO study, disaggregate models for distribution and mode choice were developed sequentially, but the models were linked by calculating a mode choice logsum for each destination alternative represented in the distribution model. Four different travel purposes were represented: home–work, home–shopping, home–social and home–other (covering education, recreation, business and pleasure ride), and car availability for purposes other than home–work was conditioned on whether car driver was chosen for the home-work trip. Validation statistics were presented which demonstrated that, in most cases, the mode choice models predict the observed mode splits by distance band well.

Daly and van Zwam (1981) describes the development of the travel demand models for the *Zuidvleugen* (South Wing) study of the Randstad conurbation in The Netherlands. The *Zuidvleugen* study created another of the earliest disaggregate model systems. Simultaneous mode-destination choice models were developed for shopping, personal business, social, recreation and other purposes.

Later developments

Algers et al. (1996) present an overview of the Stockholm Model System (SIMS). In these models, the simultaneous mode-destination model structure was extended to include models of car ownership, frequency and car allocation. For home-work, the structure was split into three substructures. In the top substructure, car ownership and workplace destination are modelled. Next, frequency, car allocation and mode choice are modelled. The lowest level substructure is the choice of whether to visit a secondary destination, and if so which destination to choose. The explicit representation of car allocation between household members in the SIMS model makes this model system a forerunner of the Activity Based Model systems that emerged in the U.S. around the turn of the century, and which are discussed briefly below.

Fox et al. (2003) summarises five different model systems that incorporate disaggregate models of simultaneous mode and destination choice. These model systems have been developed to model travel demand in The Netherlands, Norway, Paris, Stockholm and Sydney, demonstrating that simultaneous models of mode and destination choice have been used to forecast transport demands across Europe and elsewhere. These models represent between four and thirteen different modal alternatives, and between 454 and 1308 destination alternatives. The basic approach used in these models, with separate treatment of car driver and car passenger modes, explicit representation of walk and cycle mode, and car availability terms taking account of the interaction between household car ownership and licence holding, has formed the basis of the models developed for the transferability analysis presented in later chapters.

Since the turn of the century, there has been an increasing use of Activity Based Model (ABM) systems to forecast demand for transport in the U.S.. These model systems generally use disaggregate models, including models of destination choice, through it seems that the two decisions are usually modelled sequentially rather than simultaneously. For example, Jonnalagadda et al. (2001) describe separate destination choice and mode choice models which are applied in that order to model travellers in the San Francisco Bay Area. Similarly Vovsha et al. (2002) describe sequential models of destination and mode choice developed for the New York Metropolitan Transportation Council. The use of disaggregate models in ABMs has led to renewed interest into the issue of transferability, for example Sikder et al. (2013) presented comprehensive review of the spatial transferability literature in the context of ABMs.

2.1.3 Advanced model forms

Representing complex substitution patterns

In some contexts, the nested logit model has been found to be inadequate to fully represent the substitution patterns between the different modes. For example, Forinash and Koppelman (1993) found that in an intercity mode choice model, train could be nested equally well with either car or bus, and so no clear nesting structure could be established using a nested logit model. Vovsha (1997) sets out the derivation of the cross-nested logit (CNL) model, which allows for more complex substitution patterns to be represented. In the CNL structure, modes can be allocated to multiple nests using allocation parameters, so in the intercity mode choice example train could be allocated into nests with both car and bus, with the CNL estimation procedure identifying values for the allocation parameters which indicate the extent to which train falls in each nest.

Vovsha used a CNL model to develop a mode choice model for Tel-Aviv, Israel. This model had two nests, one for car modes and one for PT modes, as illustrated in Figure 2.1 where the numbers define the probability each that each modal alternative is included in the car or PT nest. It can be seen from Figure 2.1 that the park-and-ride (P&R) alternative appears in both the car and PT nests. Vovsha presents validation results for the CNL model, but does not present a comparison to results from nested logit models to illustrate the impact that moving to the CNL structure has on the substitution patterns.

Bierlaire et al. (2001) developed mode choice models from a combination of revealed and preference data that could be used to predict demand for a proposed Swissmetro service, an underground maglev system that would connect the major urban centres of Switzerland. MNL, nested logit and CNL models were estimated. 0A comparison of the model results demonstrated that the CNL model gave a significant improvement in the fit to the data, but that the value of time showed little change when the CNL structure was introduced.

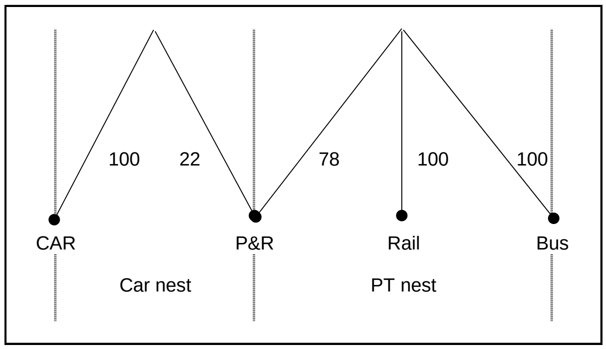

Figure 2.1: Cross-nested example, Vovsha(1997)

Representing taste heterogeneity

There has been much work in recent years in developing mixed logit models to reflect heterogeneity in tastes between individuals. In mixed logit models, rather than estimating a single value for each model parameter (the approach used in multinomial and nested logit models), for some parameters distributions are estimated to identify the distribution of tastes across individuals.

An important point to note with mixed logit is that the analyst assumes a shape for the underlying distribution of preferences. Hess et al. (2005) reviewed the different distributions that had been used at practice, finding examples of models using normal, log-normal, triangular and Johnson's S_B distributions. As Hess et al. (2005) discusses, the appropriate distribution will depend on the *a-priori* expectations for the model parameter distribution. For cost and travel time parameters, if the analyst believes that the parameter should reflect negative utility across the whole distribution, then the unbounded nature of the normal distribution precludes its use.

Daly and Carrasco (2009) investigated taste heterogeneity in models of commuter mode-destination choice for Sydney and Paris. They also made similar investigations using value of time models estimated from two sets of stated preference data collected in The Netherlands. The base MNL model specifications for Sydney and Paris used cost in logarithmic form, as this was demonstrated to give an improved fit to the data compared to a linear cost specification, and it is noted that this result has been observed in mode-destination models developed for other studies (Fox et al., 2003). The log-cost formulation implies that the marginal utility of cost decreases with increasing cost, which means that the implied values of time increase as the cost of the journey increases.

Daly and Carrasco tested for heteroskedasticity in both cost and time in model specifications with linear-cost, and in model specifications with log-cost. Both cost and time heteroskedasticity were identified, but the largest improvements in model fit were observed when in cost sensitivity was accounted for. Interestingly, when heteroskedasticity in cost was included in the Paris models, the log cost formulation was no longer better than the linear cost formulation in terms of overall fit to the data. In the Sydney case, while accounting for heteroskedasticity gave a bigger improvement in model fit in the linear-cost model, the log-cost formulation gave the best overall explanation of behaviour. The main conclusion of the paper was that the increase in VOT with trip length is more likely to be due to heterogeneity in the estimation data leading to self-selection, rather than for VOT to be increasing with distance at an individual level. For example, longer journeys are more likely to be made by faster modes, and these modes tend to be more expensive and so individuals with higher VOTs are more likely to choose them.

A number of different authors have developed mixed logit models to better explain mode choice. Bhat (1998) estimated inter-city mode choice models to predict the choice between car, rail and air on the Toronto to Montréal corridor. He identified significant heterogeneity in sensitivities to travel costs, in-vehicle times, out-of-vehicle times and frequency of service, and found that the direct rail demand elasticities were significantly higher in the mixed logit specification compared to an equivalent MNL model specification. Green et al. (2006) developed mode choice models for Sydney using stated preference data that presented a number of potential PT modes to respondents in a corridor that at that time was only served by buses. They identified significant heterogeneity in sensitivities of travellers to travel costs, in-vehicle times and egress times. Pinjari and Bhat (2006) estimated mode choice models for Austin, Texas using stated preference data that recorded choices between drive alone, shared ride, bus and rail for commuting trips. They identified significant heterogeneity in preference for two of the four modes, and in sensitivities to in-vehicle time and the unreliability of travel time.

It is clear from Daly and Carrasco's work that significant heterogeneity in tastes can exist in mode-destination choice datasets, and other researchers have found the same in mode choice datasets. The analysis presented in Chapter 8 investigates the impact that taking account of this taste heterogeneity has on the temporal transferability of the models.

2.2 Defining transferability

Koppelman and Wilmot (1982) provide the following definition of transferability which is, in the author's view, the best definition provided in the literature:

> *"First, we define transfer as the application of a model, information, or theory about behaviour developed in one context to describe the corresponding behaviour in another context. We further define transferability as the usefulness of the transferred model, information or theory in the new context."*

The first part of this definition can be interpreted quite broadly. For example, applying a model based on principles of utility maximisation assumes that those principles apply in the context in which the model is applied, as well as in the context in which the model is developed. However, the focus of the transferability literature, and of this research, is on *model transferability*. That is to say, assessing the ability of models developed in one context to explain behaviour in another context, under the assumption that the underlying behavioural theory on which the model is based is equally applicable in the two contexts.

It is interesting to note that all of the transferability papers reviewed have focussed on model transferability without considering whether changes in the applicability of the underlying economic theory are playing a role. This seems to be an area where research would be valuable.

Somewhat surprisingly, none of the other papers reviewed attempted to set out their own definition of transferability, and indeed in many cases the term is used without definition under the implicit assumption that its meaning is known to the reader.

A theme in a number of the early papers on the transferability of disaggregate models was a belief that disaggregate models, which represent choice at the individual level, should be more transferable than aggregate models, which typically represent choices at the zonal level. In some cases, claims were made for the models without much supporting evidence. For example, Ben-Akiva and Atherton (1977) claimed that:

> *"A second major advantage of the disaggregate demand modelling approach is that it is transferable from one urban area to any another. It has been hypothesised that, because disaggregate models are based on household or individual information and do not depend on any specific zone system, their coefficients should be transferable between different urban areas."*

Although the second sentence of this quote concedes transferability is a hypothesis, the first seems to treat it as a given for a transfer to any area. The argument about the zone system seems to have been made in reference to aggregate modelling approaches, which typically operate at the zonal level, but the arguments were not set out. More generally, while a number of these early papers in the transferability literature claim that disaggregate models are more transferable than aggregate techniques, only Watson and Westin (1975) empirically demonstrated that claim.

Later works, building on empirical findings that the disaggregate models were not always transferable, were more measured in their claims. Daly (1985) set out three conditions for model transferability:

- *relevance*, does the base model give any information on travel behaviour in the transfer area?

- *validity*, is the transfer model acceptably specified for the transfer area?
- *appropriateness*, is it appropriate to use the transferred model in the transfer area?

Thus models are only expected to be transferable under certain circumstances.

Along similar lines, Gunn (1985) suggested that:

> *"..a constructive definition of transferability must be based on pragmatic considerations. We assume a-priori that model parameters have different values in different contexts and consider the more general issue of whether or not an existing model provides information that can be used in some way to improve forecasting in a new context."*

A key distinction is made in the literature is between *temporal transferability* and *spatial transferability*. Temporal transferability is concerned with the application of models developed using data collected at one point in time at another point in time, whereas spatial transferability is concerned with the application of models developed using data from one spatial area in another spatial area. Usually temporal transfers take place within the same spatial area, and spatial transfers take place at or around the same point in time. However, in some cases a model is transferred over both time and space and so the two categories are not mutually exclusive.

To consider temporal and spatial transferability in the context of disaggregate mode destination choice models, it is useful to define in summary form the utility functions used in the models:

$$U_{md} = \beta X + \varepsilon_{md} \tag{2.19}$$

where: U_{md} is the utility of mode-destination alternative md
β is a vector of model parameters

X is a vector of observed data

ε_{md} is the random error term

In model development, the objective is to identify model parameters that best explain the observed data. Thus, as a model is developed, and its ability to explain the observed choices increases, the term βX increases in importance, and the term ε_{md} decreases in importance. Nonetheless, mode destination models do not perfectly explain the observed choices, and so some random error remains. The mean contribution of the random term is captured in the mode specific constants, which in a mode choice context will capture effects such as the relative reliability of modes, levels of comfort, climate and hilliness for walking and cycling, and so on.

In a spatial transfer at the same point in time, the transferability of the model will depend on the relevance of the parameters in the transfer context, for example the degree of similarity in sensitivities to travel time and cost, and on the appropriateness of the alternative specific constants. Models would be expected to be transferable for areas that have similar characteristics, such as similarities in mean travel times and costs, levels of highway and public transport reliability, climate, hilliness and so forth.

For a temporal transfer in a given area, the considerations are different. The effect of area to area differences is not present, instead the key issue is whether the parameters remain constant over time. Stated more explicitly, the issue is whether within a given population segment, the sensitivities to the different variables that form the utility functions, and the mean contribution of unmeasured effects as measured by the alternative specific constants, remain constant over time. In some instances, the ratio between model parameters is also important. For example, the value-of-time implied by the ratio between the cost and time parameters in a model, which will change over time if there are changes in the cost and time parameters.

Thus temporal and spatial transferability are not the same thing. A model might be temporally transferable within a given area, but contain a specification that does not transfer well to other areas. Another model might contain a detailed specification that transfers well to other spatial areas, but does not transfer well over time.

Spatial transfers typically involve a *transfer sample*, a sample of choices observed in the transfer context, which may allow a locally estimated model to be developed for comparison with the model transfer. When a model is applied to forecast behaviour, this is a transfer of the model to a new temporal context. However, unlike many spatial transfers, no transfer sample is available. There is, therefore, an important practical difference between temporal and spatial transfers.

Temporal transferability can be assessed, however, by using two datasets collected at different points in time from the same spatial area. Typically one dataset is historical, one is contemporary. Models estimated from the two samples can be compared to make assessments of model transferability, and from these, conclusions can be drawn about the temporal transferability of similar models used for forecasting. The current research is concerned with the transferability of models over long-term forecasting horizons of 20-plus years, and therefore requires datasets collected up to twenty years apart.

This research is concerned with the temporal transferability of mode destination models over long-term forecasting horizons. It is worth emphasising that over such forecasting horizons, key model inputs, such as population, employment and travel times and costs on the networks, will be subject to considerable uncertainty, and different assumptions can have substantial impacts of the predictions of future travel behaviour. Thus, temporal transferability is a factor in producing the best possible forecasts of future behaviour, but is certainly not the only consideration.

2.3 Assessing transferability

Many of the approaches for assessing transferability identified from the literature rely on the availability of a transfer sample, which is used to develop a *locally estimated model*, and then the transferred model is assessed relative to this locally estimated model. This allows the performance of the two model specifications to be compared statistically in the transfer context.

The measures of transferability used in the literature can be placed into three categories. First are statistical tests, discussed in Section 2.3.1.

The second category is measures that look at changes in individual parameters, or groups of parameters, which are summarised in Section 2.3.2. These measures provide insight into the transferability of different parameters in a model which in turn informs assessment of the robustness of model forecasts for different types of policy intervention.

The third category is predictive measures, described in Section 2.3.3, which are assessments of the predictive ability of a model in the transfer context. Predictive measures can be used to make assessments of model transferability, but they do not necessarily directly measure transferability because errors may follow from errors in forecasting the input variables, and so measures of this type need to be interpreted with caution. The issue of the need to disentangle errors in the input variables from model transferability is discussed further in Section 2.3.3.

A fourth category has been added in this research, namely calculation of model elasticities which are discussed in Section 2.3.4. These provide a measure of the overall sensitivity of a model to changes in key policy variables such as travel costs and travel times.

2.3.1 Statistical tests

A frequently used statistical test in the literature is the Transferability Test Statistic (TTS), which assesses the transferability of the base model parameters β_b in the transfer context t, under the hypothesis that the two sets of parameters are equal:

$$TTS_t(\beta_b) = -2(LL_t(\beta_b) - LL_t(\beta_t)) \tag{2.20}$$

where: $LL_t(\beta_b)$ is the fit (log-likelihood) of the base model to the transfer data
$LL_t(\beta_t)$ is the fit for the model re-estimated on the transfer data

TTS is chi-squared distributed with degrees of freedom equal to the number of model parameters. It can be seen that this test is the same as the standard likelihood ratio test but applied to pairs of log-likelihood values in a different context. An early example of the application of this test in the context of model transferability is a mode choice transfer study by Atherton and Ben-Akiva (1976), though the TTS terminology seems to have been coined by Koppelman and Wilmot (1982).

The TTS measure was widely used in the early transferability literature, but as discussed in Section 2.3.3 this measure has nearly always rejected the hypothesis of model transferability, including cases where the model has been found to have good predictive ability in the transfer context (for example the analysis of Badoe and Miller (1995a) reviewed in Section 2.4.1).

It should be noted that in general the TTS statistic is not symmetrical, i.e. for a given set of base and transfer samples it is possible to accept transferability in one direction but reject it in the other. So transferability may be accepted for the base model applied to the transfer data, but that is no guarantee that the same model specification estimated on the transfer data will be transferable to the base data. In forecasting, models only used to predict forward in time, but assessments of model transferability can be made using data collected at two points in time, and in these instances transfers can be made both forward and back in time to maximise the number of tests made.

The Transfer Index (TI) measures the predictive accuracy of the transferred model relative to a locally estimated model, with an upper bound of one. A reference model is used in the calculation of TI, typically a market shares model in the case of mode choice.

$$TI_t(\beta_b) = \frac{LL_t(\beta_b) - LL_t(\beta_t^{ref})}{LL_t(\beta_t) - LL_t(\beta_t^{ref})} \tag{2.21}$$

where: β_t^{ref} is the reference model for the transfer data
$LL_t(\beta_t) \geq LL_t(\beta_b) \geq LL_t(\beta_t^{ref})$

This measure was devised Koppelman and Wilmot (1982), and the use of a simple market shares model was relevant to their assessments of mode choice models. However, this research is specifically concerned with mode-destination models, and in this context a more appropriate measure of a base model performance should include some fit to trip length and ensure proportionality to the attraction variables *ceteris paribus* [5],. This can be achieved by specifying a reference model with utility functions as follows:

$$V_{md}^{ref} = \delta_m + \beta_m^{dist} dist_{md} + \gamma \, log(A_d) \tag{2.22}$$

where: V_{md}^{ref} is the utility function for alternative md
δ_m is a mode-specific constant for mode m

[5] i.e. that the probability of choosing a destination is proportional to the attraction variables, all other things being equal.

β_m^{dist} is a distance parameter for mode m

$dist_{md}$ is the distance to destination d by mode m

γ is the log-size multiplier

A_d is the attraction variable

Unlike the TTS, the TI does not either accept or reject the hypothesis of model transferability. Rather it provides a relative measure of model transferability. Within a given study area, the TI can be used to directly assess different sets of models. When comparing between different studies, the TI still provides insight provided the same reference model specification is used, but the TI does not have a general scale in a formal sense.

2.3.2 Changes in individual parameters

The statistical measures discussed so far are concerned with the overall fit to the data, but differences in individual parameter values are also of interest. For example, the cost and time parameters in a model are key to the forecast responses to policy, and so changes in these parameters over time are of particular relevance.

In cases where both base and transfer model parameters are available, such a comparison should correct for scale differences between the two models. Scale differences result from different levels of error and result in differences in the magnitude of the parameters, in particular if a model has more error then the parameters will be smaller in magnitude. Correcting for this scale difference allows the parameters to be compared on a consistent basis, an issue which is discussed further in Section 2.5.2.

A number of papers in the literature, particularly those concerned with transfer methodologies, use the term 'transfer bias' ξ, which is simply the difference between base and transfer parameter values:

$$\xi = \lambda\beta_t - \beta_b \tag{2.23}$$

where: λ is a scale parameter to account for differences in error between the base and transfer models
(if λ is not known it may be set to one, i.e. assuming no change in scale)

If the base and transfer parameters are β_b and β_t respectively then, assuming the covariance to be zero, the standard error of the difference can be calculated as:

$$\sigma(\beta_t - \beta_b) = \sqrt{(\sigma[\beta_b])^2 + (\lambda\sigma[\beta_t])^2} \tag{2.24}$$

where: $\sigma[\beta_b]$ is the standard error of β_b
$\sigma[\beta_t]$ is the standard error of β_t

In the context of tests of temporal transferability the assumption of zero covariance is reasonable, because the choice samples used at different points at time are collected from different people and so it is reasonable to assume that their choices are not correlated.

The t-ratio for the parameter difference is then calculated as:

$$t(\beta_t - \beta_b) = \frac{\lambda\beta_t - \beta_b}{\sigma(\beta_t - \beta_b)} \tag{2.25}$$

If the t-ratio exceeds a critical value, such as 1.96 for a 95% confidence interval, then the null hypothesis H_0 that the parameters are identical is rejected. An important point to note when interpreting results from this test is that the higher the standard deviations of β_b and β_t, the more likely it is that the null hypothesis will be accepted. So β_b and β_t could be substantially different in magnitude, but due to low parameter significance in one or both of the parameters the null hypothesis that the parameters are identical could be accepted. An alternative to calculating the significance of parameter differences is to calculate the change in absolute parameter magnitude, accounting for scale differences between the base and transfer contexts. To do this the relative error measure (REM) can be calculated using as:

$$REM_{\beta} = \frac{(\lambda\beta_t - \beta_b)}{\beta_b} \tag{2.26}$$

2.3.3 Predictive measures

Building on early empirical findings that transferred models usually failed strict statistical tests of transferability, predictive measures were increasingly used to assess transferability as the transferability literature developed. For example, Lerman (1981) argued that the early transferability literature had used an excessively restrictive definition of transferability with an over-emphasis on statistical tests, and argued that transferability should not be seen as a binary issue but rather that the extent of transferability should be explored. In the same book, Ben-Akiva (1981) argued that achieving perfect transferability is impossible, as a model is never perfectly specified, and therefore pragmatic transferability criteria are required in addition to standard statistical tests. Daly and Gunn (1983) made similar arguments, arguing against simple accept or reject statistical tests of transferability in favour of more pragmatic measures.

Predictive measures need to be interpreted carefully when making assessments of model transferability. In cases where both base and transfer samples are available, then provided both datasets provide accurate samples of individual choices, the ability of the base model to predict choices in the transfer context is a direct test of the transferability of the model.

However, in many studies that validate model predictions against observed aggregate outcomes detailed transfer samples are not available, and the model forecasts are validated against aggregate mode shares. In these studies, the predictions of the model depend on the accuracy of the assumed inputs as well as the transferability of the model itself. So, a model may be highly transferable, but if fuel prices dramatically increase during the forecast period, and this was not anticipated when the future inputs where assembled, the model predictions may be some way off the observed outcomes. Care needs to be taken to distinguish input errors from transferability errors, and in some cases it is not possible to disentangle the two effects. This issue has been considered in the review of temporal and spatial transferability literature presented later in this chapter. In the empirical analysis presented in later chapters, historical data has been used and as such input data was available for each year of data, which means that and the input errors issue does not arise (assuming that the input data is accurate).

This section goes on to set out a series of measures that have been used in the literature to measure the predictive performance of models in order to provide some assessment of model transferability.

The relative error measure (REM) for the prediction of choice frequency in some aggregate group can be calculated as:

$$REM_{mg} = \frac{(P_{mg} - O_{mg})}{O_{mg}} \tag{2.27}$$

where: P_{mg} is the prediction for alternative m in group g

O_{mg} is the observed choices for alternative m in group g

The difference between Equation 2.27 and Equation 2.26 is that Equation 2.26 is concerned with changes in individual parameter values whereas Equation 2.27 is concerned with changes in demand.

It should be noted that g is often dropped, i.e. predicted and observed alternative (e.g. mode) shares are compared but the analysis is not split into separate groups. As the REM measure is self-scaling, it can be applied both to probabilities, and to aggregate choice predictions such as numbers of individuals choosing m and g.

Although the REM measure is widely used, it can cause problems with division by zero if there are no observed choices in group mg. To overcome this problem a modified measure REM^* can be used:

$$REM^*_{mg} = \frac{(P_{mg} - O_{mg})}{P_{mg}} \tag{2.28}$$

The use of P_{mg} rather than O_{mg} for the denominator avoids problems of division by zero when there are no observations but predicted probabilities are non-zero.

2.3.4 Model elasticity

A measure that has received little consideration in the model transferability literature is model elasticity, that is to say the sensitivity of the model to changes in key input variables, usually travel times and costs. If demand for alternative j is D_j, then the elasticity η_{jx} for a change in a variable x can be calculated as:

$$\eta_{jx} = \frac{x}{D_j}\frac{dD_j}{dx} \tag{2.29}$$

An important advantage of elasticities are that they are dimensionless, which means they can be compared between different model systems, or between model systems and evidence from other data.

Frequently elasticities are computed by observing the changes in demand in response to a given change in an input variable. Standard UK practice as set out in the Department for Transport's WebTAG guidance[6] is to use a log form for the elasticity calculations:

$$\eta_{jx} = \frac{log(D_j^0 - D_j^1)}{log(x^0 - x^1)} \tag{2.30}$$

Equation 2.30 has been used in the analysis presented in Chapter 6.

Elasticities are an important measure for model validation, as they provide a check that the model sensitivity is in line with accepted values. In the UK context, the Department of Transport sets out expected elasticity values for realism testing, in particular for fuel cost where kilometrage elasticities values in the range -0.25 to -0.35 are expected based on the work of Bradburn and Hyman (2002).

However, elasticities are also important for model transferability as they define the sensitivity of the model to changes in travel costs and time. In the UK context, a model may give fuel cost elasticities in the expected range in the base context, but if the elasticities change when the model is used in forecasting the model sensitivity may no longer be acceptable. Many transport demand models in the UK are applied using a pivot approach, whereby the model is applied in both base and forecast contexts to define growth factors applied relative to base matrices generated from count data. In this context, the key role of the demand models is to provide the sensitivity of the model system to cost and time changes,

[6] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/373137/webtag-tag-unit-m2-variable-demand-modelling.pdf, accessed 19/04/15.

and elasticities provide a measure of this sensitivity.

Daly (2008) considered the relationship between elasticity, model scale and error. He explored the apparent paradox that improving the model specification would be expected to increase the model scale, as the error would be reduced, but this could potentially increase the sensitivity of the model. Daly demonstrated that when a model is improved by adding a variable, provided that the change does not introduce a bias to the the other coefficients, no change in sensitivity is expected. This is because model sensitivity depends on the variance of the predicted probabilities among the population, as well as to the magnitude of the model coefficients. If the variance in the probabilities increases, as it will when variables are added to the model, that will reduce model sensitivity and this compensates for the change in the magnitude of the model coefficients. However, if a variable is introduced which causes bias then this can impact on the model sensitivity.

Following UK practice set out in the UK Department for Transport's WebTAG guidance, four elasticity measures have been calculated in the analysis presented in Chapter 6:

- fuel cost kilometrage elasticity
- car time trip elasticity
- PT fare trip elasticity
- PT in-vehicle time trip elasticity

In a mode-destination choice model, a kilometrage elasticity will be impacted by changes in both mode and destination, whereas trip elasticities are driven by mode choice responses alone.

It should be emphasised that there is no expectation that elasticities will be completely stable over time. As well as being influenced by changes in the cost and in-vehicle time parameters, changes in the data will impact on the model elasticities. For example, given the non-linear treatment of cost in the models changes in the distribution of costs between different years of data would be expected to impact on the elasticity values. The approach that has been used is to compare the elasticities for a base model applied in the transfer context to the transfer model (i.e. the same model specification re-estimated in the transfer context).

2.3.5 Assessing temporal transferability

This section sets out how the various measures of transferability identified from the literature have been used in the context of this particular research, and then discusses the practical difficulties involved in assessing temporal transferability over the long term.

In terms of statistical measures, providing definitions of the TTS and TI is important before presenting the reviews of temporal transferability in Section 2.4 and spatial transferability in Section 2.5, as these two measures have been used extensively to assess model transferability. The t-ratio test for the significance of differences in particular parameters over time has been applied to provide additional analysis of the temporal stability of individual parameter values reported across different studies, and to investigate across studies whether certain groups of model parameters exhibit greater stability than others.

In the empirical analysis undertaken for this research, emphasis has been placed on the TI measure, as it provides a measure of the ability of a transferred model to predict observed behaviour relative to a locally estimated model. Selecting an appropriate reference model is important for the TI measure to be able to effectively discriminate between base and transfer models, and this is why the reference model in Equation 2.22 has been formulated specifically for this research.

In terms of predictive measures, the REM measure has been used to compare parameter values between base and transfer contexts, as well as to compare observed and predicted mode shares. Model elasticities in the base and transfer contexts have also been compared to investigate changes in model sensitivity over time.

Together, these measures give a toolkit that can be used to make assessments of transferability. However, there are practical issues in making assessments of temporal transferability that are relevant for forecasting. If a model is used to make a forecast 20 years into the future, then this forecast cannot be validated for another 20 years, and even where such evidence exists it is problematic, because the predicted inputs in terms of population and level-of-service will differ from what actually happened.

An option that was considered was to make backcasts, e.g. to apply a model developed using contemporaneous data to predict what was observed to happen in the past using known information on level-of-service and attractions. The difficulty is that this will highlight differences between model predictions and observed data, but it does not allow the analyst to fully explore them. For example, a model applied in backcasting may over-predict the historic car share, but that does not provide insight into which models terms contributed to that over-prediction. Greater insight would be gained by an approach that explored how the model parameters varied between the two points in time.

A more insightful way to investigate transferability is to use detailed interview data collected at two points at time so that models can be developed for both time periods and differences analysed. As will be seen in Section 2.4, this approach has been widely used in the transferability literature. It has the advantage that it allows for statistical tests of transferability and analysis of changes in individual parameters over time as well as tests comparing observed and predicted changes in mode share and trip length, and is therefore the approach that has been used for the empirical analysis in this thesis.

2.4 Temporal transferability

The literature on temporal transferability has been broken down into three sub-sections. The first two sub-sections discuss studies using disaggregate mode or mode-destination choice models, and thus are more directly relevant than the other literature to the objectives of this research. Section 2.4.3 then presents evidence from other model types, in most cases aggregate models of trip generation.

The mode choice studies are further broken down into direct tests of model transferability (Section 2.4.1), where both base and transfer models have been developed allowing formal statistical tests of transferability to be made, and validation studies (Section 2.4.2), where model predictions are compared to aggregate statistics on mode share, often after substantial changes to travel times and/or costs. It should be noted that these validation studies use data collected in the transfer context to define the inputs to the models, which removes the complication of combinations of errors in the input data discussed in Section 2.3.3. A number of the papers present both comparisons of base and transfer models, and use the transfer data to validate the performance of the base model in forecasting, and so are discussed in both sections.

2.4.1 Mode choice transferability studies

Summary of studies reviewed

Ten studies of the transferability of mode choice models have been reviewed, all of which analysed home–work trips. These studies are summarised in Table 2.1.

Table 2.1: Temporal mode choice transferability studies

Paper	Area	Time frame	Degree of transferability	Comments
Train (1978)	San Francisco, U.S.	3 years (1972-1975)	LOS parameters more stable than other terms	
Silman (1981)	Tel-Aviv, Israel	4 years (1972-1976)	Good, time parameters particularly stable	
McCarthy (1982)	San Francisco, U.S.	1.5 years (1973/74-1975)	Parameters stable over short-term	Box-Cox transforms used
Kozel (1986)	Bogota, Columbia	6 years (1972-1978)	Travel time transferable, but cost and socio-economic terms not	
Badoe and Miller (1995a,b); Badoe and Wadhawan (2002)	Toronto, Canada	22 years (1964-1986)	Statistical differences between parameters but models but broadly transferable in terms of predictive performance, ASCs and scale change over time	Level-of-service only models performed well, some highly segmented models less transferable
Sanko (2014a,b)	Nagoya, Japan.	30 years (1971-2001)	Parameters not transferable	Missing variables believed to contribute to poor transferability
Forsey et al. (2012)	York region, Toronto	5 years (2001-2006)	Good in predicting mode share	
Habib et al. (2012)	Toronto	5 & 10 years (1996, 2001, 2006)	Travel time stable but significant changes in cost sensitivity	
Habib and Weiss (2014)	Toronto	5 & 10 years (1996, 2001, 2006)	Mode choice preference structures not stable over time	Models represent modal captivity

Overall, these mode choice studies supported the hypothesis that model parameters are reasonably stable over time, although this finding was not universal with three of the ten studies reporting substantial changes over time.

In addition to these ten mode choice studies, two studies have investigated the transferability of models of simultaneous mode and destination choice, the exact focus of this research. Karasmaa and Pursula (1997) used Helsinki data from 1981 and 1988, and Gunn (2001) investigated models for the Netherlands using 1982 and 1995 data. Like the ten mode choice studies, Karasmaa looked at home–work trips only, but Gunn ran analyses for home–work, home–shopping and home–social and recreational travel.

The findings from these two studies were mixed. Gunn's study was supportive of the hypothesis of parameter stability, however in Karasmaa's analysis there were significant differences between the base and transfer parameters. Neither of these two studies presented statistical test of overall model transferability.

Impact of model specification

Badoe and Miller made tested seven different model specifications to investigate the impact of model specification on model transferability, ranging from simple market shares models, and models with mode constants and level-of-service variables only, through to models with detailed market segmentation. For all model specifications, the TTS rejected the hypothesis of parameter stability at a 5% confidence interval. However, the TI increased from 0.132 for the simple market shares model, to 0.894 in the level-of-service variables only model, although interestingly more detailed specifications with market segmentation had lower TI values, despite higher log-likelihood values, possibly due to over-fitting to the base data.

Overall, Badoe and Miller concluded that improving model specification improves model transferability.

Findings from studies which have estimated models by pooling data over years

Badoe and Wadhawan compared the transferability of model specifications jointly estimated from 1964 and 1986 data compared to models estimated using 1986 data alone by investigating how well the various models explained mode choices observed in 1991 data. Comparing the various pooled model specifications, they found that higher transferability was obtained if separate mode constants were estimated for each year of data, and if separate scales were estimated for level of service and socio-economic terms to take account of differential changes in the scale of different groups of utility terms between years. However, the best disaggregate predictions of the 1991 mode choices were obtained from models estimated from 1986 data alone. So the conclusion from this study would be that the best approach for forecasting is to apply a model from the most recently available cross-section of data, rather than jointly estimate models by supplementing recent data with older data.

Sanko investigated how best to combine data from 1971, 1981 and 1991 to predict the mode choices observed in 2001. Testing separate models by year first, he found that the 1991-only model was best at predicting the 2001 choices, whereas the 1971-only model was worst, therefore confirming the expectation that the most recent available data should be used for forecasting. Next, he tested models estimated by pooling 1971, 1981 and 1991 data. In the first pooled model, the data was pooled naïvely without estimating any year specific constants or scale terms. In the second pooled model, constants, scales for level of service terms and scales for socio-economic terms were estimated separately by year, and then the scales and constants for 1991 were used to apply this model to predict the 2001 mode choices. Interestingly, both of these pooled models performed worse in predicting the 2001 mode choices than the 1991-only model. The finding that the best results are obtained using the most recent data only is consistent with

Badoe and Wadhawan's analysis.

Variation in transferability with model purpose

As noted above nearly all the studies focussed on home–work travel alone, and thus Gunn's study is the only one that allows some assessment of differences in model transferability with model purpose. In addition to results for commuting, Gunn (2001) presented results for shopping, and social & recreational travel. Analysis of the changes in the parameter values is presented in Table 2.2 using the REM measure defined in 2.26, and the full results by purpose reported by Gunn are presented in Appendix A.

Table 2.2: Cross purpose comparison of temporal parameter stability

	LOS Terms		Socio-Econ Terms	
Purpose	Terms	REM	Terms	REM
Commuting	6	0.21	2	0.13
Shopping	6	0.47	2	0.44
Social & recreation	6	0.64	2	0.02

Considering first the level-of-service terms, the commute model results are the most transferable of the three, i.e. have the lowest mean REM measure. For the two socio-economic terms reported in each model, the social & recreational results are the most transferable.

It is not possible to draw general results from this single comparison, but the results give some indication that the transferability of models may vary with purpose, and it is possible that conclusions based on commuting models alone may overstate the transferability of models in general.

Cross-study analysis of changes in individual parameter values

Most of the studies reported the base and transfer model parameters in full, and these have been analysed to investigate whether there is any evidence across studies that certain types of model parameters are more transferable than others. To perform this analysis, the parameters were grouped into alternative specific constants, level-of-service parameters (including cost), and socio-economic terms[7]. The detailed analysis is presented in Appendix A.

The REM measure presented in Equation 2.26 was used to analyse changes in parameter magnitude. The following average values were calculated by parameter group:

- cost parameters: 0.71
- level-of-service parameters: 0.59
- socio-economic terms: 0.56
- mode constants: 1.10

These results demonstrate that the socio-economic and level-of-service parameters are the most transferable, and as might be expected the constants were the least transferable parameter group. Given that many transport policies involve changes to travel times and costs, the higher temporal stability of the level-of-service parameters (which includes in-vehicle time parameters) is noteworthy.

Statistical tests of the changes in parameter values were also made using Equation 2.25. The hypothesis of parameter stability was accepted more often in the Train and Silman studies, where the transfer periods are 3 and 4 years, than in the other studies where longer transfer periods were considered, suggesting higher parameter transferability over shorter transfer periods [8].

[7] Where level-of-service parameters are interacted with socio-economic variables, e.g. cost divided by income, the parameters have been placed in the level-of-service group.

[8] In the Forsey study, the estimation samples were large and as consequently most of the parameters were highly significant. As a result, the hypothesis of parameter stability was rejected even in comparisons where the two parameters were relatively close in magnitude.

2.4.2 Mode choice validation studies

Summary of studies reviewed

The studies that were reviewed are summarised in Table 2.3.

As noted in the introduction to this section, all these validation studies used detailed transfer data, and therefore are not confounded by errors in the input variables. Nonetheless, an important caveat must be made in terms of interpreting an ability to predict mode shares accurately with model transferability. It is possible to accurately predict mode shares with a model that is not temporally transferable. For example, consider the common problem of correlation between car cost and car time variables. It is possible to estimate a model that underestimates the importance of one of these variables, and overestimates the other. It may be that in a given application, the errors associated with two these terms cancel out, and that accurate forecasts are obtained, but in other applications with difference combinations of cost and time changes the model forecasts may contain substantial errors. Thus the ability to accurately predict mode shares is an indication of model transferability, particularly if demonstrated over a number of applications, but is not a strict test of it.

The general pattern from these studies is that the mode choice models were able to predict the impact of often substantial changes in level-of-service on mode share with reasonable accuracy. This finding is reassuring for the application of mode choice models over periods of up to five years, but it does not provide any direct evidence about the transferability of the models over the longer term.

Milthorpe (2005)'s study had a different focus, providing a comparison of the forecasts of a four-stage model[9] developed in the early 1970s to observed data from around 2001.

[9] i.e. a model with generation, distribution, mode choice and assignment components.

Table 2.3: Temporal mode choice validation studies

Paper	Area	Purpose(s)	Time Frame	Predictive Performance	Comments
Parody (1977)	Univ. of Amherst, Mass., U.S.	Commute	4 waves: 1. Autumn 72 2. Spring 73 3. Autumn 73 4. Spring 74	Good, substantial improvement when model specification improved with socio-economic terms	Large changes in modal costs over time period
Ben-Akiva and Atherton (1977)	Washington D.C., U.S., Santa Monica U.S. (application only)	Commute	D.C. 1970-74 S.M. 1974	Good in response to significant changes in LOS	Focus on car-pooling policies
Train (1978, 1979)	San Francisco, U.S.	Commute		Poor for transit due to problems with input data, predictions improve with improved model specification	Lack of info. for new BART mode, erroneous walk time data
Silman (1981)	Tel-Aviv, Israel	Commute	4 years (1972-1976)	Mixed - main car driver and bus modes predicted well, minor car passenger mode signif. overpredicted	

Impact of model specification

Parody's analysis used panel data, and in one test assessed the impact of substantial increases in parking charges. In this test, a full model specification with socio-economic parameters performed substantially better than a model with level-of-service parameters alone. This suggests that an improved model specification yielded more transferable level-of-service parameters. Train's 1979 analysis also concluded that improving the model specification resulted in improvements in the model predictions.

It seems that the improvement in the predictive performance of the models that results from adding socio-economic parameters is a result of improved estimates of the key level-of-service parameters, rather than the impact of changes in socio-economics, given that most of these model tests have been undertaken over short term forecasting horizons of up to five years. These improved estimates then enable the models to better predict the impact of changes in level-of-service. Silman explicitly noted this pattern, by observing that when socio-economic parameters were added, the significance of the key cost and time variables in his models were improved.

Parameter transferability in the context of errors in the forecasts of the input variables

Milthorpe discussed in his paper that he would have liked to be able to have been able to re-run the original 1970s model with actual 2000 inputs, but that this was not possible because the detailed coding was not available. Instead, Milthorpe compares the different scenario predictions of the model with observed data. A noteworthy point that Milthorpe highlights is the degree of uncertainty of key input variables over a 30-year forecasting horizon. Table 2.4 summarises figures from Milthorpe's paper that highlight this point.

Table 2.4: Socio-demographic growth in Sydney, 1971 to 2001

	Predicted	Observed
Population	55%	35%
Household size	-10%	-17%
Workforce	47%	40%
Vehicles	149%	123%

It can be seen that over a 30 year horizon, the predictions of key input variables can be subject to considerable uncertainty. These results help to put model transferability into context; if, for example, the errors due to changes in the true parameters in Sydney impact on model predictions by $\pm$10% over a 30-year period, this should be assessed against an over-estimate of the population of 14%, and of the number of vehicles of 11%.

2.4.3 Other studies

Summary of studies reviewed

The majority of the other studies reviewed were generation models. The generation model studies are summarised in Table 2.5.

Table 2.5: Temporal generation model studies

Paper	Area	Model Class	Purpose(s)	Time Frame	Evidence for Transferability?	Comments
Hill and Dodd (1966)	Toronto, Canada	Zonal regression	All purposes, all purposes peak hour	8 years (1956–1964)	Yes, after correcting for differences in data processing	Actual results after correction applied unclear
Kannel and Heathington (1973)	Indianapolis, Indiana, U.S.	Household regression	All purposes	7 years (1964–1971)	Yes predicted trips within 2% of observed	Panel of household used, this may have influenced findings
Downes and Gyenes (1976)	Reading, U.K.	Zonal regression, category analysis, hh regression	All purposes, plus split into shop, work, other	9 years (1962–1971)	Yes, forecasting errors close to base year errors	
Yunker (1976)	S.E. Wisconsin, U.S.	Zonal regression analysis	Commute, shopping, other, non-home-based	9 years (1963–1972)	Good predicted growth close to observed, larger differences by purpose	Observed trips grew by 25% in period
?	Detroit, Michigan, U.S.	Category analysis, hh regression	All purposes	12 years (1953–1965)	No, trip rates not stable uniform growth over categories	Uniform growth likely to be income and/or accessibility
Doubleday (1977)	Reading, U.K.	Aggregate, category analysis	Regular (work) and non-regular	9 years (1962–1971)	Trip rates not stable, exception was employed males	Accessibility had an impact, and possibly income growth
Badoe and Steuart (1997)	Toronto, Canada	Household level regression	Commute, shopping, social & recreational and pers. business	22 years (1964–1986)	Commute models gave reasonable predictive performance, other purposes poor	
Cotrus et al. (2005)	Haifa, Tel Aviv, Israel	Person level regression	All purposes	12/13 years (1984–1996/97)	Mixed, statistically rejected, but predictions good with 7% and 3% errors	
Shams et al. (2014)	New York region, U.S.	Multinomial logit	Commute & shopping	12/13 years (1998–2010/11)	Statistical tests accept for commute but reject for shopping	

Transferability findings

Most of these studies are concerned with generation modelling, and typically used aggregate modelling approaches, based on regression, household classification and gravity model techniques. As such, any findings with respect to model transferability have to be interpreted with caution for the mode-destination modelling context. Nonetheless, general findings are of interest to the broader question of whether models developed at one point in time can be used to predict behaviour at a future point in time. These studies also have the advantage that they have tended to consider longer forecasting intervals, typically around 10 years, compared to the mode choice studies.

Few of these studies made formal statistical tests of model transferability. Elmi concluded that the parameters in his trip distribution models were statistically different between 1964 and 1986, although the 1964 models were able to predict 1986 behaviour well. Cotrus also rejected the hypothesis of temporal stability, both in Haifa and in Tel Aviv, over a 12/13 year period. Interestingly Shams *et al.* accepted the hypothesis of parameter stability for their commute models, but rejected it for their shopping models, and Badoe and Steuart found that commute models had much better transferability than home–shopping, home–social & recreational and home–personal business models.

The assessments of the predictive performance of the generation models are supportive of the hypothesis of model transferability, with six of the nine studies reporting the models predicted future trip generations well. It should be noted however that, as discussed in Section 2.4.2, accurate aggregate predictions do not necessarily indicate transferability at the individual parameter level.

A noteworthy feature of many of the tests of the generation models is that the intervals of analysis often covered substantial changes in population, whereas the mode choice validation studies were typically concerned with the impact of substantial changes in travel cost and times. For example, Hill and Dodd's analysis covered a period when the population of the Greater Toronto area increased by 33%, and total car ownership rose by 45%. The good predictive performance of the models under these conditions provides some evidence for the temporal stability of socio-economic parameters that capture variation in behaviour across the population.

Other studies

Elmi et al. (1997)'s analysis of work trip distribution models investigated the impact of improving the model specification, and, consistent with the mode choice studies, he concluded that improved model specification resulted in improved model transferability. Elmi obtained Transferability Indices as high as 0.84 for predicting 1996 behaviour with 1964 models, and 0.97 for predicting 1996 behaviour with 1986 models. An interesting result noted by Elmi was that the disutility of travel time reduced over time, from a value of -0.13 in 1964 to -0.08 in 1996. Elmi suggested that this reflected changes in spatial structure, and consequent increases is the mean distance to work.

Chingcuanco and Miller (2012) and Miller estimated a meta-model to explain changes in vehicle ownership model parameters over time as a function of macroeconomic variables, specifically fuel prices and the employment rate. They were able to identify significant relationships between these variables and the alternative specific constants in their vehicle ownership model, for both the unadjusted values of the variables and for the change in the variable relative to the previous year.

2.5 Spatial Transferability

Studies that have investigated spatial transferability provide some evidence about the transferability of disaggregate mode choice models in general. Disaggregate models are expected to be more transferable than aggregate models because observed choices are explained as far as possible in terms of behavioural model parameters, and the behavioural parameters should be applicable in different contexts. However, as discussed in Section 2.2, it is important to emphasize that a model that is spatially transferable may not be temporally transferable, and vice-versa. The spatial transferability literature is also useful in developing methods that are useful for making assessments of model transferability, and so the review presented here focuses on these methods.

There is a body of evidence on mode choice models that dates from the mid-1970s, and this forms the focus for this section. In most cases, both base and transfer samples were available in these studies, and so statistical tests of transferability were reported. The review is split into a discussion of the findings with respect to spatial transferability, and a discussion of papers which investigated different methodologies for transferring models. In particular, the section on methodology discusses transfer scaling, a technique that has been developed for undertaking spatial transfers, but which could yield interesting findings for the assessment of temporal transferability.

Recently the issue of spatial transferability has returned to the fore in the context of activity based models (ABMs). As Sikder et al. (2013) note:

> *"..given that ABMs are more behaviorally orientated, there is a notion in the field that these would be more transferable than the statistical correlations reflected by aggregate four-step models"*

Literature exists on the spatial transferability of generation models, however given that the generation models are not the focus of this research, and nor is spatial transferability, this literature has not been reviewed here.

2.5.1 Mode choice transferability studies

The mode choice transferability studies that have been reviewed are summarised in Table 2.6.

Results of formal statistical tests of transferability, which use the Transferability Test Statistic (TTS) given in Equation 2.20, are mixed. Table 2.7 summarises the results, in each case at a 95% confidence level.

Taken as a whole, and referring back to Section 2.2, these results are evidence that spatial transferability only holds in certain cases, and in many cases does not hold. However, as discussed in Section 2.3.3 the TTS provides a strict pass/fail test of transferability and for temporal transfers Badoe and Miller (1995a) observed good predictive performance in the transfer context from models that failed the TTS test.

Some authors sought to explain why the models they tested were not transferable according to the TTS measure. Galbraith and Hensher concluded that it was because there were unmeasured effects represented in the constants, and that analysts should aim to include more variables to account for socio-economic effects, 'unmeasured' level-of-service attributes, and situational or contextual factors which explain travel behaviour. However, the type of effects that are typically captured in the constants, such as perceptions of comfort, safety, the impact of weather on walk and cycle modes and so on, are by their nature difficult to measure. Thus, while there are currently efforts underway to better represent the impact of reliability on mode choice, a typical mode choice model today will nonetheless contain a similar model specification to the models developed by Galbraith and Hensher 25 years ago.

Table 2.6: Spatial transferability tests - mode choice models

Paper	Area	Purpose(s)	Survey Dates	Degree of Transferability	Comments
Watson and Westin (1975)	Glasgow, U.K.	Inter-city trips	1974 or earlier	Mixed, transferability varied according to O and D region	Improved model specification may have improved transferability
Atherton and Ben-Akiva (1976)	Wash. D.C., New Bedford and L.A., U.S.	Commute	D.C.: 1968 N.B.: 1963 L.A.: 1967	Good, esp. for LOS parameters	Useful to update model parameters when transfer
Talvitie and Kirshner (1978)	Washington, Minneapolis-St Paul, Bay Area	Commute	D.C.: 1968 Minn.: 1970 BART: 1972,75	Poor using statistical criteria	60-80% of explanatory power explained by constants
Koppelman and Wilmot (1982)	Washington D.C., U.S.	Commute	1968	Rejected statistically, but predictive measures suggest models are transferable	Transfer effectiveness substantially improved when constants updated
Galbraith and Hensher (1982)	Sydney, Australia	Commute	1971 and 1975	Rejected statistically, 2 out of 3 models performed well using predictive measures	Unmeasured effects captured in constants believed to underlie result
Gunn et al. (1985)	Rotterdam and the Hague (base), Utrecht, Netherlands	Personal business, shopping	Rott. and Hag.: 1977 Utrecht: 1982	Successful using transfer scaling – performance close to local models	Transfer scale and constant estimated
Daly (1985)	Grenoble (base) Nantes, France	Commute, education	Grenoble: 1978, Nantes: 1980	Successful for home-work, mediocre for home-edu.	Transfer scale and constant estimated
Koppelman et al. (1985)	Washington D.C., U.S.	Commute	1968	Half diff. between full transfer and local estimation from updating constants, smaller gain from updating model scale	Explicit test of scaling approach
Koppelman and Wilmot (1986)	Washington D.C., U.S.	Commute	1968	High when constants are adjusted, improving model specification improves transferability	Explicit test of impact of model specification on transferability
Abdelwahab (1991)	Canada	4 inter-city	1984	Rejected in 7 out of 8 comparisons	
Dissanayake et al. (2012)	Bangkok & Manila	All purposes	1996	Rejected	Travel cost omitted from model specification

Table 2.7: TTS statistics for spatial transfers

Author(s)	Transfer Between	TTS Results
Watson and Westin (1975)	Area type combinations	6 fail, 8 pass
Atherton and Ben-Akiva (1976)	Two cities	Pass
Talvitie and Kirshner (1978)	Four cities	All fail
Galbraith and Hensher (1982)	Two regions	Fail for 3 model spec.s
Koppelman and Wilmot (1986)	Three city sectors	Fail for all 3
McCoomb (1986)	Between four cities	2 fail, 2 pass
Abdelwahab (1991)	Two regions	Fail for 7/8 tests
Dissanayake (2012)	Bangkok & Manila	Fail

Koppelman and Wilmot investigated whether improving model specification improves model transferability, and found that this was indeed the case. Referring back to Equation 2.19, improving the model specification should increase the impact of the explanatory variables, and reduce the impact of unmeasured effects captured in the constants. When a model is transferred to a new area, the explanatory variables will capture differences between the areas, such as differences in travel times, and socio-economic differences if these are represented in the models. By contrast, transferring the alternative specific constants implicitly assumes that the average effect of unmeasured effects is the same in base and transfer contexts.

2.5.2 Mode choice methodological studies

A number of papers in the methodological class investigate an approach termed *transfer scaling* Gunn et al. (1985); Gunn (1985); Daly (1985); Koppelman et al. (1985); Gunn and Fox (2005), and it is useful to describe what is meant by this in more detail. In spatial transfers, it is normal for both base and transfer samples to be available, although the latter may be small in magnitude or sparse in detail. If the base model is transferred to the new context without adjustment, then the transfer is said to be *naïve*. In the transfer scaling approach, scales are estimated for utility parameters, or groups of parameters, to express the changes relative to the base estimates.

Two types of transfer scaling approach have been applied. First, where an overall utility scale is estimated to re-scale the complete set of base model parameters, which is termed a *complete transfer*. Second, where a number of utility scales are estimated to re-scale groups of base model parameters, which is termed a *partial transfer*. In both cases, the original base model parameters are held fixed during the transfer. These two approaches can be expressed in equation form as follows:

$$V_{t,c} = \delta_t + \phi_t \, \beta_b \, X_t \tag{2.31}$$

where: $V_{t,c}$ is the transfer utility for a complete transfer
δ_t is the alternative-specific constant
ϕ_t is the transfer scale
β_b is a vector of the base parameter estimates
X_t is a vector of observed data in the transfer context

and:

$$V_{t,p} = \delta_t + \phi_{t,1} \, \beta_{b,1} \, X_{t,1} + ...\phi_{t,G} \, \beta_{b,G} \, X_{t,G} \tag{2.32}$$

where: $V_{t,p}$ is the transfer utility for a partial transfer
δ_t is the alternative-specific constant
$\phi_{t,g}$ is the transfer scale for utility group g
$\beta_{b,g}$ is a vector of the base parameter estimates for utility group g
$X_{t,g}$ is a vector of observed data in the transfer context
there are $g = 1, G$ groups of utility terms in total

It should be noted that in the complete transfer approach, the relative trade-offs between parameters, such as between the cost and time parameters, are preserved in the transfer. In the partial transfer approach, the parameter trade-offs are preserved within each utility group.

The transfer scaling studies have demonstrated that applying transfer scaling yields substantially more transferable models than naïve transfer of the base model parameters. This improved performance comes about for two reasons. First, the ability to account for different levels of error in the set of parameters as a whole, or for groups of model parameters, between base and transfer contexts. Second, by adjusting the constants and therefore accounting for differences in the average contribution of unmeasured effects.

Gunn and Fox (2005) estimated significantly different transfer scales for different groups of utility terms: for car and walk/cycle, for public transport, and for other level of service terms. Grouping utility terms in this way is an approach that allows generalisable results to be drawn out as to the transferability of different utility terms, and it is an approach that can be used to investigate temporal transferability in cases where both base and transfer samples are available.

2.6 Summary and aims

2.6.1 Summary of the evidence for temporal transferability

Overall, the direct tests of transferability summarised in Table 2.1 are supportive of the hypothesis that mode choice models can be transferred over time, with the majority of studies concluding the models tested were transferable. Furthermore, some of the validation studies demonstrate the models are able to predict the impact on mode share of substantial changes in level-of-service over short periods.

That said, these findings are specific to the evidence base that has been analysed. Considering the direct tests of temporal transferability summarised in Table 2.1, it can be seen that the evidence is nearly all from commuting studies. Furthermore, all the validation studies in Table 2.3, and many of the generation studies in Table 2.5, are also based on commuter travel. Commuting travel might be expected to be more transferable than other purposes, as the journey to work is a regular trip, and as such would be expected to be accurately recorded with a higher degree of accuracy than less regular trips.

Another feature of the evidence base is that much of it is based on short-term forecast of up to 10 years. This research is concerned with long term transferability for forecast periods of 20 years and above, and it seems reasonable to hypothesise that over longer time intervals transferability would be less likely to be accepted. The two studies that provide evidence on longer term transferability give mixed findings, the studies from Toronto that developed mode choice models and distribution models are supportive of model transferability, whereas the mode choice models developed for the Nagoya region of Japan are not (though the Nagoya results are likely to have been influenced by the lack of cost and car availability information).

An empirical finding from both mode choice and distribution studies is that improving model specification improves model transferability. Although the improvements in model specification described are often the addition of socio-economic parameters, this improvement in model performance seems to come about because the improved models provide better estimates of the key cost and time parameters that respond to short-term policy changes. Over a longer term forecasting horizon, substantial changes in the distribution of the population across segments would be expected, and so the findings in terms of model specification may be different, depending on the relative stability of level-of-service and socio-economic parameters over the longer term.

It is noted that only two studies of temporal transferability have considered simultaneous models of mode and destination choice, the focus of this particular research. Their findings were mixed: Gunn (2001) found a good level of temporal transferability, but in Karasmaa and Pursula (1997) three out of four level-of-service parameters were not transferable.

As discussed in Section 2.1.3, there has been much work in recent years to develop mixed logit models to reflect taste heterogeneity. While this work has demonstrated the improved fit to the base data that these specifications can offer, none of the transferability studies reviewed in Sections 2.4 and 2.5 used model specifications including random taste heterogeneity. Evidence as to whether models incorporating random taste heterogeneity are more transferable, and thus better specified to make forecasts, would be valuable to model developers.

In summary, providing further empirical evidence on the temporal transferability of mode-destination choice models over intervals up to 20 years, and with a comparison of commute and non-commute travel, would add to the existing literature. There is some limited evidence that there may be differences in transferability by parameter type (e.g. alternative specific constants, level-of-service terms, socio-economic terms) and it would be useful to further investigate such differences during the analysis. Furthermore the transferability of models incorporating random taste heterogeneity is an area where research would be valuable.

2.6.2 Aims

Drawing on the findings from the literature review, five specific research aims were identified to provide a framework for the empirical work:

1. to assess the transferability of mode-destination choice models over long-term forecasting horizons of up to 20 years;

2. to assess the relative transferability of commuter and non-commuter travel;
3. to investigate how model scales and alternative-specific constants evolve over time, both in total, and for model scale distinguishing utility groups in order to enable assessment of the relative transferability of utility groups and the constants;
4. to investigate the transferability of mode-destination choice models that take account of preference heterogeneity; and
5. to advise practitioners how best to specify models to maximise their temporal transferability.

Chapter 3

Data

This chapter begins in Section 3.1 by setting out the data that is required to assess the transferability of mode-destination models over long-term forecasting horizons.

Section 3.2 describes the Toronto data that was used to allow transferability analysis. It starts by describing the mode-destination choice data, goes on to describe the other data assembled including level of service data defining travel costs and times by the various modes modelled, and then concludes by summarising the processing steps undertaken by the author and by others to prepare the data for model estimation.

Section 3.3 presents the corresponding information for the Sydney data.

The chapter concludes in Section 3.4 with a brief summary of the key differences between the two datasets and the implications that these have for the transferability analyses presented in Chapter 5–8.

3.1 Introduction

In order to investigate the transferability of mode-destination models over long-term forecasting horizons, determining the availability of suitable data was a crucial issue for this research. The data requirements were as follows:

- data collected over long-term horizons of up to 20 years;
- household interview data, with household, personal and trip level data, with survey and data documentation, and with sufficient similarity between surveys that the same model specifications can be applied to each year of data;
- level of service data for each year, using identical zoning systems, or zoning systems with similar levels of data[1]; and
- zonal attraction data by year, with population and employment data.

Level of service (LOS) data is best visualised as matrix data, with rows as possible origin zones and columns as possible destination zones, and individual cell values providing an indication of the LOS for travel by a particular origin-destination pair. For car driver and car passenger modes, highway level of service data is generated by running assignments to highway networks that represent the road network for the study area. The level of service matrices generated typically comprise travel times and distances, plus any tolls that may be payable. Often, in the absence of a dedicated representation of walk and cycle links, distances from the highway network are used to represent distances for the walk and cycle modes. For public transport modes, separate assignments are run to a public transport network. More LOS components are represented, including in-vehicle times, walk access/egress times, wait times (possibly split between first and other wait time) and numbers of transfers.

[1]New zones are often added as cities expand or redevelop, therefore identifying areas that have used identical zoning systems for all years of data may not be possible.

The LOS requirements for developing mode-destination choice models are more onerous than those for mode choice models because for a given origin zone it is necessary to have LOS information to each possible destination, whereas in a mode choice model LOS information is only required for the chosen destination. Therefore historical datasets that have been used to investigate the transferability of mode choice models do not necessarily contain sufficient LOS data to allow mode-destination models to be estimated.

The highway and public transport networks are developed using dedicated software packages such as Emme, VISUM, Saturn, Cube Voyager and Omnitrans. In any large metropolitan area in the developed world, it would be expected that the local agency responsible for transport planning in the region would own and maintain highway and public transport models. However, it is much less likely that these agencies will maintain old networks from 20 years back, and that if they do that those networks were developed and coded in a consistently with the current network models. Thus, the requirement for consistent assignments from over a 20 year period is the most challenging of the data requirements set out above.

Two metropolitan areas were identified where the required data was available, and crucially a local contact was supportive of the research effort and made the data available for analysis, specifically Toronto, Canada, and Sydney, Australia. The Toronto data was analysed first using nested logit models, and then the Sydney data was used to investigate whether the two datasets yielded consistent findings. Finally, the Toronto data was analysed again to investigate the transferability of mixed logit models of mode-destination choice. Given that the datasets were analysed in this order, details on the two datasets are presented in this chapter rather than in chapters specific to each dataset.

The other datasets that were investigated are described below.

Data from Helsinki has been used in a number of transferability studies, such as the work reported in Karasmaa and Pursula (1997); Karasmaa (2003). From the two papers reviewed, it is clear that household interviews exist for Helsinki in 1981 and 1988, with around 6000 interviews in both cases. Further a 1995 mobility survey was used in Karasmaa's PhD work. Attempts were made to contact Karasmaa to investigate whether they would be willing to make the data available for analysis. However, it turns out Karasmaa has now left the Helsinki University of Technology, and that since Karasmaa left the institute has not taken forward research on temporal transferability. Permission to use the data for analysis was not forthcoming.

Data from the Netherlands was used for early research into model transferability. However, it is not clear whether the earlier data can be retrieved, and so when it became clear that data from both Toronto and Sydney would be available for analysis this dataset was not pursued further. Similarly the author has been involved in modelling studies using disaggregate data in Copenhagen (Vuk et al., 2009) which might have been suitable, but that were not pursued further once the Toronto and Sydney datasets were confirmed as being available.

Finally, a large household travel survey has been collected in Montréal, Canada, every five years since 1970, and some researchers have used this to compare travel behaviour in Toronto and Montréal (Roorda et al., 2008). However, it is not clear whether supporting level of service information is available for this data, and a complication is that the relevant documentation is in French. Were level of service data to be available, a useful addition to the analysis presented in this thesis would be for a Francophone analyst to repeat and extend the analysis using the Montréal data.

3.2 Toronto

The Toronto data is ideally suited to transferability analysis because large household interviews have been conducted repeatedly, collecting the same set of information at different points in time. Furthermore, supporting level-of-service and attraction data is available for each year of data. The following sub-sections describe the choice, level-of-service and attraction data that was assembled for the modelling and transferability analysis.

3.2.1 Choice data

Toronto Transportation Tomorrow survey

The Transportation Tomorrow Survey (TTS) is a comprehensive travel survey conducted in the Greater Toronto and Hamilton Area (GTHA) that has been collected once every five years[2]. The first TTS, conducted in 1986, obtained completed interviews for a 4.2% random sample of all households in the GTHA. The 1991 survey was a smaller update of the 1986 survey focusing primarily on those geographic areas that had experienced high growth since 1986. The survey area was expanded slightly to include a band approximately one municipality deep surrounding the outer boundary of the GTHA for the purpose of obtaining more complete travel information in the fringe areas of the GTHA.

The 1996 TTS was a new survey, not an update. Agencies outside of the GTHA were invited to participate. The survey area was expanded to include the Regional Municipalities of Niagara and Waterloo, the counties of Peterborough, Simcoe, Victoria and Wellington, the Cities of Barrie, Guelph, and Peterborough and the Town of Orangeville.

[2] www.dmg.utoronto.ca/transportationtomorrowsurvey/index.html, accessed 20/12/10.

The 2001 TTS was essentially a repeat of the 1996 survey. The survey area was the same as in 1996 except for the exclusion of the Regional Municipality of Waterloo and inclusion of City of Orillia and all of the County of Simcoe.

Similarly, the 2006 TTS was another repeat of the 1996 survey with approximately 150,000 completed interviews. The survey area was the same as in 2001 except for the inclusion of the Regional Municipality of Waterloo, the City of Brantford and the County of Dufferin.

Table 3.1 summarises the samples sizes in each TTS survey, detailing the number of households, persons and trips recorded. Table 3.1 also details the household sample rate, and the total number of households and persons in the survey areas. It is noted that for the 1991 TTS differential sampling rates were used for high and low growth areas.

Table 3.1: TTS sample sizes and survey area populations

	1986	1991	1996	2001	2006
TTS households	61,653	24,507	115,193	136,379	149,631
TTS persons	171,086	72,496	312,781	374,182	401,653
TTS trips	370,248	157,349	657,951	817,744	858,348
% households sampled	4.2%	5.0% high 0.5% low	5.0%	5.6%	5.2%
Total households	1,466,080	1,709,557	2,317,190	2,417,513	2,871,245
Total persons	4,062,642	4,729,193	6,285,142	6,529,615	7,705,341

It is noted that Toronto household interview data also exists that was collected back in 1964, and this data has been used by other researchers to investigate the transferability of mode choice models (Badoe and Miller, 1998). However, to estimate models of mode-destination choice, level-of-service matrices defining transport conditions for all possible combinations of origin and destination are required. Level-of-service matrices of this type were not available for the 1964 data, and therefore it could not be used for this particular analysis.

Extent of TTS data

As noted above the TTS data collected has changed over time in extent, specifically the geographical coverage of the data has expanded, and the person, household, and trip data collected in the TTS has undergone some changes over time.

In order to transfer the base models to the various transfer datasets, it is necessary to base the transferability analysis upon a dataset definition which is supported by both the base data and all of the transfer datasets.

The evolution of the geographic extent of the data is summarised in Table 3.2 and illustrated in Figure 3.1 and 3.2.

Table 3.2: Evolution of geographical extent of TTS data

1986	1991	1996	2001	2006
Greater Toronto & Hamilton Area (GTHA)	Greater Toronto & Hamilton Area (GTHA)	Greater Toronto & Hamilton Area (GTHA)	Greater Toronto & Hamilton Area (GTHA)	Greater Toronto & Hamilton Area (GTHA)
	One municipality ring around GTHA	One municipality ring around GTHA	One municipality ring around GTHA	One municipality ring around GTHA
		Niagara municipality	Niagara municipality	Niagara municipality
		Waterloo municipality		Waterloo municipality
		Counties of Peterborough, Simcoe, Victoria and Wellington	Counties of Peterborough, Simcoe, Victoria and Wellington	Counties of Dufferin, Peterborough, Simcoe, Victoria and Wellington
		Cities of Barrie, Guelph, Peterborough and the Town or Orangeville	Cities of Barrie, Guelph, Peterborough and the Town or Orangeville	Cities of Barrie, Brantford, Guelph, Peterborough and the Town or Orangeville

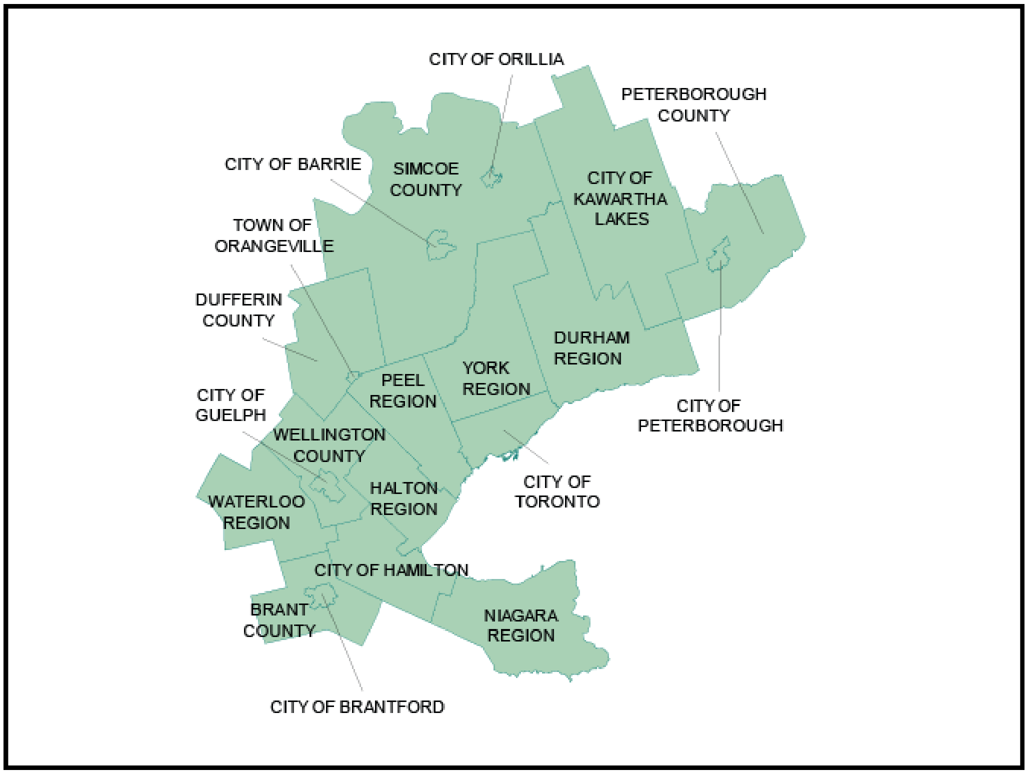

Figure 3.1: Areas surveyed in TTS data

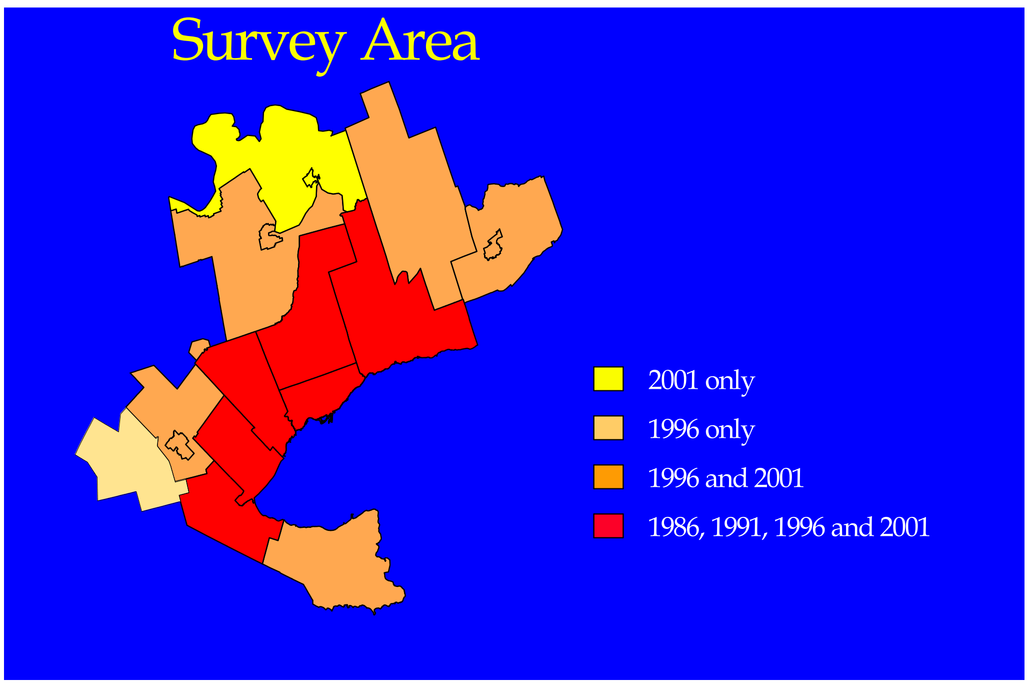

Figure 3.2: Variation in area surveyed by year

For the transferability analysis, only GTHA data has been used in order that the same geographic definition applies across both base and transfer datasets, and therefore level of service data defined for the GTHA area only was required. The extent of the GTHA area is indicated by the red area in Figure 3.2.

In 1986, bicycle trips were only recorded in the trip data for work and education trips. From 1991 onwards, bicycle trips were recorded for all travel purposes. For the home–work transferability analysis it was originally intended that bicycle trips be included. However, in the processed trip files supplied for this analysis bicycle trips were not included, and therefore bicycle trips were excluded from both the home–work analysis[3].

Finally, it is noted that the availability of free parking at work information was not collected in the 1986 surveys.

Another consideration is differences in sampling strategy. The 1986 and 1996 surveys were based on a random selection of households throughout the survey area (4.2% in 1986, 5.0% in 1996) (Data Management Group, 2008). However, the 1991 survey used different sampling rates for high and low growth areas. The target was 5% in the high growth areas and 0.5% in the low growth areas such as the City of Toronto. The 2001 and 2006 surveys sampled around 5% of households with the sample selection based on Forward Selection Areas, based on the first three characters of the post code. Given that the 1991 survey is considerably smaller than the other surveys it was decided to drop the 1991 data from the transferability analysis.

Table 3.3 summarises the data definition for the transferability analyses.

[3]Except for the 2001 data, where bicycle trips are coded together with walk trips.

Table 3.3: Toronto home–work transferability analysis data definition

Geographical area	Greater Toronto and Hamilton area
Years of data	1986, 1996, 2001, 2006
Bicycle trips	Excluded, except 2001 where merged with walk
Free parking at work	Missing for 1986

TTS sample sizes

Given the dataset definitions provided in Table 3.3, Table 3.4 details the samples of trips available for the transferability analyses.

Table 3.4: TTS sample sizes for transferability analysis

	1986	1996	2001	2006
TTS home–work trips	52,154	63,865	79,371	72,893
TTS households	61,453	88,898	113,608	112,486
TTS persons	171,086	243,286	315,202	305,696
Expanded households	1,466,080	1,805,021	1,975,155	2,160,059
Expanded persons	4,062,642	4,926,367	5,386,137	5,871,885

It can be seen that the samples of home–work trips available for analysis are substantial, with at least 50,000 records available from each of the four years of data.

It had been hoped to also use samples of home-other travel trips from the TTS data so that the transferability of home–other travel models could be compared to the transferability of home–work models. However, while samples of home–work trips had already extracted for the development of mode choice models for the GTHA area, trip samples had not been extracted for other purposes. While it would be possible to extract these trip samples from the TTS data, resources were not available in Toronto to extract the data required and therefore the Toronto transferability analysis has been undertaken using the home–work trip samples alone.

The expanded person totals show that the population of the GTHA has grown by 45% between 1986 and 2006. This rapid growth is relevant for the transferability analysis, because it means many people have migrated into the GTHA region since 1986. The assumption when applying models developed using 1986 data to predict travel behaviour in later years is that the parameters estimated to explain the travel choices of the 1986 GTHA population apply equally to newcomers to the GTHA region. Similar assumptions apply to models transferred from different base years. The population of Toronto is forecast to continue to grow rapidly, with an additional 2.6 million people and 1.4 million jobs expected between 2001 and 2031 (Jewell and Wyatt, 2013), and so models estimated from current residents need to be transferable to those who migrate into Toronto over the coming decades.

3.2.2 Level of service and attraction data

The other data used in the model estimations is level-of-service and attraction data. Both types of data are defined using the model zoning system, and so this section starts with a discussion of the changes to the model zoning system over the period that TTS data is available, and considers the likely impact of these changes on the transferability analyses.

Changes to model zoning system

The number of travel zones used in the models varies between the four different years of TTS data, as additional travel zones have been added over time. Table 3.5 summarises the changes in the number of travel zones over time.

Table 3.5: Number of travel zones by year of TTS survey

Year	Travel zones	Increase from 1986
1986	1404	n/a
1996	1677	19.4%
2001	1717	22.3%
2006	1845	31.4%

The 1404 zones used to model the 1986 data are defined in the 1991 GTHA zoning system. The 1996 data is modelled using the 1996 GTHA zoning system, which relative to the 1991 GTHA zone system incorporated substantial revisions to the traffic zones for the City of Toronto, York Region and Durham Region, and more minor changes to the traffic zones in the Peel and Halton Regions (Data Management Group, 1998). The 2001 data is modelled using the 2001 GTHA zone system. This is similar to the 1996 GTHA zone system, but with some minor modifications in the City of Toronto, Peel Region and Halton Region (Data Management Group, 2003). Finally, the 2006 data is modelled using the zoning system developed for the Hurontario model. The Hurontario zone system is based on the 2001 GTHA zone system, but contains more detailed zoning in the Hurontario corridor, and some zones in Hamilton and Durham have been aggregated into larger zones. Thus outside of the Hurontario corridor, the zone systems used to model the 1996, 2001 and 2006 datasets contain similar levels of detail, whereas the zone system used to model the 1986 data is slightly more aggregate.

The use of a more detailed zoning system should result in more accurate level-of-service measures, particularly when considering access to local transit and distances for the walk mode. Therefore, *ceteris paribus* we would expect more accurate level-of-service measures for the 1996, 2001 and 2006 datasets relative to the 1986 data.

Level-of-service data

The transferability analysis has been undertaken for models of simultaneous mode and destination choice. The base and transfer choice data files supplied provide LOS for the chosen destination, but in order to model destination choice for a trip with a given origin zone it was necessary to have LOS information for all possible destination zones. This implied the need for LOS matrices for all possible combinations of origin and destination zone. These LOS matrices define the LOS based according to the results generated by assignment models, rather than by collecting observed LOS from individuals in the TTS data.

Fortunately, significant analysis has already been undertaken at the University of Toronto to allow mode-choice models to be developed for each year of the TTS data. As a result of this previous work, LOS data was readily available for each of the four years of TTS data selected for analysis. The 1996 LOS data is described in more detail in Miller (2001). The combination of large repeated cross-sectional surveys collected over a 20-year period with readily available LOS data for each survey meant that the Toronto data provided the ideal dataset for investigating temporal transferability.

Consistent with standard transport planning practice, LOS was generated separately for highway and transit modes. The LOS supplied so far is for a peak hour assignment to an AM-peak network, which has been used in the modelling under the assumption that all commute travel is made during peak times. LOS has been supplied separately for each modelled year.

The highway assignments have been undertaken in Emme/2 for each modelled year. The following LOS information is available for an AM-peak period assignment:

- travel time (mins)

- travel cost (kilometre cost plus any toll, \$)
- toll (\$)

It is noted that a fixed cost per kilometre is used to calculate the distance related component of car costs. As a result, the distance in km can be inferred by subtracting the toll from the total travel cost, and dividing by the cost per kilometre which is constant for a given year. Tolls only exist in the 2006 networks. The fixed costs per kilometre are summarised in Table 3.6. The costs are all presented in 1986 prices so that the impact of real growth in prices over time is clear.

Parking costs are supplied separately in the form of average daily parking costs by zone. These costs are zero for most zones, with non-zero costs defined for the CBD and other central areas only. Consistent with home–work mode-choice models developed in Toronto, half the average daily parking cost at the destination zone has been assumed in the home–work models. This approach assumes half of individuals have to pay the parking costs, and the other half of individuals have access to free parking at their destination. The mean average parking costs represented in the models for zones with non-zero parking costs are also summarised in Table 3.6.

Table 3.6: Car costs, 1986 prices

	1986	1996	2001	2006
Distance related cost (cents/km)	4.70	4.76	5.43	8.30
Change relative to 1986	n/a	1.3%	15.6%	76.5%
Zones with non-zero parking cost	6.1%	7.5%	81.0%	7.2%
Mean parking cost in these zones (\$)	2.37	1.92	1.18	1.92
Change relative to 1986	n/a	-18.9%	-50.2%	-18.7%

It can be seen that real car costs per kilometre rose slowly between 1986 and 2001, but then there was a significant increase in 2006 due to increases in fuel prices. Parking costs declined by nearly 20% between 1986 and 1996, and then remained essentially constant in real terms between 1996 and 2006. The parking cost data that was supplied for 2001 is very different to the other years, with non-zero parking costs defined in the majority of zones, rather than just central zones. As a result, the average contribution that parking costs make to total car costs is significantly higher in the 2001 data.

The transit assignments have been undertaken in Emme/2. The following information has been supplied for an AM-peak period assignment:

- transit fare ($)
- transit in-vehicle time (mins)
- transit wait and transfer time (mins)
- transit walk access and egress time (mins)

Treatment of inflation

All costs in the models have been expressed in 1986 prices. To convert costs into 1986 prices, Consumer Price Indices (CPI) values assembled by Statistics Canada have been used (Statistics Canada, 2008). The CPI values for the years of TTS data that have been modelled are summarised in 3.7.

Table 3.7: CPI values (2002=100)

Year	CPI
1986	65.6
1996	88.9
2001	97.8
2006	109.1

Attraction data

The attractiveness of each destination alternative is defined using an attraction variable, which for commute trips is total employment. The employment information was taken from Census journey to work data, which is collected every 5 years in Toronto, and as such is expected to provide an accurate estimate of the actual number of jobs in each travel zone.

3.2.3 Processing steps

The choice data was supplied by Prof. Eric Miller of the University of Toronto. The data was supplied in text file format as home–work trip records with limited person and household information appended. These trip files had been used previously for the development of home–work mode choice models.

Some processing was required to convert the choice data files into a format suitable for use by the ALOGIT estimation software, where each line of input data must contain the specified number of variables in numeric format. The files were also sorted by home zone to facilitate the appending of level-of-service information.

The level-of-service data was also received as text files, and so processing steps were setup to convert the data to the matrix format used by the ALOGIT estimation software.

The attraction data was supplied as text files which could be read directly into ALOGIT without the need for intermediate processing.

3.3 Sydney

3.3.1 Choice data

The Sydney choice data has been taken from two sets of household interview data. The first is a large household interview survey collected in 1991, named the Household Interview Survey (HIS). The HIS data was collected between 30$^{\mathrm{th}}$ September 1991 and 3$^{\mathrm{rd}}$ October 1992. Face to face surveys were undertaken which recorded all travel made by all household members during a 24-hour period, and each day of the year was equally represented in the survey (Transport Study Group, 1996).

From 1997 onwards, the data collection strategy in Sydney was changed and a continuous survey was begun. The continuous survey data is named the Household Travel Survey (HTS), and is organised in one year waves which run from July to June the following year. The HTS survey collected similar trip, person and household information to the HIS survey, and was again collected using face to face interviews (Bureau of Transport Statistics, 2012).

In both the HIS and HTS data, detailed person and household information has been collected, allowing the development of more detailed socio-economic segmentations than are possible with the Toronto TTS data. A particular advantage of the Sydney data is that incomes were collected and therefore the Sydney data can be used to investigate whether mode-destination models that segment cost sensitivity with income are more transferable than models with no income segmentation. For this analysis, four waves of HTS data collected between July 2004 and June 2008 have been used to represent 2006 travel choices. This allows model transferability to be assessed over a 15 year transfer period.

Both the HIS and HTS data were collected across the Sydney Statistical Division

(SD), the Newcastle Statistical Sub-Division (SSD) to the north, and the Illawarra SD to the south. However, the tour samples and LOS data for the HIS data were only available for households interviewed in the Sydney SD. Therefore for the transferability analysis, only data from the Sydney SD is included so that the spatial definition is consistent between the years of data. Figure 3.3 illustrates the area surveyed in the HIS and HTS data, and in particular the extent of the Sydney SD that forms the study area for the Sydney transferability analysis.

In Figure 3.3, GMA is Greater Metropolitan Area, and NSW is New South Wales.

Figure 3.3: Sydney study area

Table 3.8 summarises the samples sizes and study area populations. The 1991 household and person totals are taken from Castles (1993). This publication gives figures for occupied dwellings rather than households and will therefore underestimate the number of households as some dwellings will contain more than one household.

Table 3.8: Sydney SD sample sizes for transferability analysis

	1991 HIS	2006 HTS
Home–work tours	5,111	5,173
Home–other travel tours	8,717	10,464
Sampled households	9,955	10,423
Sampled persons	28,398	28,559
Total households	1,222,568	1,572,117
Total persons	3,538,749	4,215,393

The total population has grown by 19% between 1991 and 2006. While this is not as high as the 46% growth observed in the Toronto population between 1986 and 2006, it still represents a high level of population growth compared to European cities.

3.3.2 Level of service and attraction data

The other data used in the model estimations is LOS and attraction data. Both types of data are defined using the model zoning system, and so this section starts with a discussion of the changes to the model zoning system between 1991 and 2006 data, and considers the possible impact of these changes on the transferability analyses.

Changes to zoning system

As illustrated in Table 3.9, the number of model zones used to represent the Sydney SD increased by a factor of 2.7 between 1991 and 2006.

Table 3.9: Number of travel zones by year of Sydney survey

Year	Travel zones	Increase from 1991
1991	845	n/a
2006	2,277	170%

The use of a substantially more detailed zoning system for the 2006 data should result in more accurate LOS measures, especially for access to public transport modes, and for the walk and cycle modes where tour lengths are lower. However, it has been suggested by researchers in Sydney that the change in zoning system results in lower distances on average. Specifically, Xu and Milthorpe (2010) analysed Census Journey to Work data between 1981 and 2011 and found a steady increase in mean tour length over time except over the 2001 to 2006 interval which was the period over which the move to the much more detailed zoning system was made.

The Transport Data Centre at the New South Wales Department of Transport have provided more detail on this issue. For the 2006 network, there were generally four connectors per model zone whereas the 1991 network is understood to have had one to two. The lower number of connectors in the 1991 network will tend to result in shorter tours, particulary for short distance tours where the connector length is a higher fraction of the total distance.

The impact of these changes is illustrated in 3.10 and 3.11, which show the changes in the mean distances by mode, with distances for all modes measured using the highway distance skims impacted by the zone connector issue.

Table 3.10: Sydney home–work distances by mode (km)

Mode	1991	2006	change
car driver	33.2	29.4	-11%
car pass.	26.1	20.9	-20%
train	62.7	51.6	-18%
bus	19.7	18.7	-5%
bike	12.9	11.4	-11%
walk	4.3	3.1	-28%
taxi	15.1	17.8	18%
Total	33.8	29.7	-12%

Table 3.11: Sydney home–other travel distances by mode (km)

Mode	1991	2006	change
car driver	16.9	13.1	-22%
car pass.	19.4	14.4	-26%
train	55.8	46.3	-17%
bus	18.1	11.3	-38%
bike	8.2	6.0	-26%
walk	4.2	2.2	-48%
taxi	16.4	12.2	-26%
all modes	16.4	11.9	-27%

It can be seen that with the exception of taxi for home–work, mean distances measured by the highway network consistently reduce. Furthermore, the reductions are greater for home–other travel where tours are shorter, and for modes such as walk and cycle where tour distances are shorter. Furthermore, Transport Data Centre (2008) present analysis of the mean trip lengths in the same 1991 and 2006 data using a different set of distances measures that does not show the same reduction in mean trip distance.

Level of service data

To develop simultaneous models of mode and destination choice from the Sydney data it was necessary to assemble LOS measures for highway and public transport modes. These were supplied in the form of matrices defining the LOS between each pair of travel zones in the Sydney SD. LOS was available from 1991 and 2006 Emme network models developed by the Bureau of Transport Statistics at Transport New South Wales, which they kindly made available for use in this research. The LOS and other information was also readily available for the HIS data because mode-destination models were developed from a combination of the HIS data and the early waves of the HTS data in 2000 (Milthorpe et al., 2000). Similarly LOS and other information was available for the 2004–2008 data because mode-destination models have recently been developed using this data (Fox et al., 2011).

For highway, LOS measures were available separately by four time periods:

- AM peak, 07:00–08:59
- inter-peak, 09:00–14:59
- PM peak, 15:00–17:59
- off-peak, 00:00–06:59, 18:0–23:59

To take account of impact of congestion in the periods adjacent to the peaks, LOS for the 'shoulder' periods of 06:00–06:59, 09:00–09:59, 14:00–14:59 and 18:00–18:59 was calculated by taking an average of the LOS in the period adjacent the peak and the LOS in the peak.

The following LOS information was supplied for each of the four time periods:

- free flow travel time (mins)

- congested travel time (mins)
- distance (km)
- toll ($)

The modelling work in 2000 to develop mode-destination models from the HIS data used fixed costs per kilometre to model fuel and non-fuel car costs, and those values have been retained in this analysis. The models developed in 2000 were extensively updated in 2010 (Fox et al., 2011), and in the updated models a more detailed advanced approach was used to calculate fuel costs as a function of the mean speed for the OD pair. However, parameter values for the more detailed approach were not available for 1991. If the more detailed approach was used for 2006 but not 1991, this could bias the transferability analysis. Therefore, the average fuel cost per kilometre given by the detailed approach was calculated from the estimation samples, and then this fixed cost per kilometre was used in the transferability analysis models. Table 3.12 summarises the car costs per kilometre used in the models.

Table 3.12: Car costs, 1986 prices

	1991	2006	change
Fuel cost (cents/km)	6.55	12.0	83.6%

It can be seen that real car costs have increased substantially between 1991 and 2006, consistent with the trend in the Toronto data observed in Table 3.6.

For public transport (PT) modes, only AM peak assignments were available, and it is has been assumed that these can be used to model PT trips made at all times of the day. This assumption is more reasonable for commute tours, which tend to be made during the peak periods, than for discretionary travel, which is more likely to take place during the inter-peak and off-peak periods. LOS from two PT networks was used in the modelling. The first is a bus-only network, used to model PT tours where the only PT mode used in bus. The second is all all PT modes network, which includes rail, light rail and ferry modes. Note that bus can form an access or egress mode in the all PT modes network.

The following LOS information was supplied from the bus-only network:

- fare ($)
- in-vehicle time (mins)
- walk access and egress time (mins)
- first wait time (mins)
- other wait time (mins)
- boardings

For the all PT modes network, the following information was supplied:

- fare ($)
- rail in-vehicle time (mins)
- light rail in-vehicle time (mins)
- ferry in-vehicle time (mins)
- bus in-vehicle time (mins)
- walk access and egress time (mins)
- first wait time (mins)
- other wait time (mins)
- boardings

Treatment of inflation

All costs in the models have been converted into 1991 prices. The CPI values for the years of data that have been modelled are summarised in Table 3.13.

Table 3.13: CPI values (1989/90=100)

Year	CPI
1991	106.7
2004/05	147.3
2005/06	151.0
2006/07	155.8
2007/08	159.5

Attraction data

The attraction data for the commute models is total employment. For the other travel models, a combination of different attraction variables were used, population and service employment. All of the attraction data was assembled by the Bureau of Transport Statistics.

3.3.3 Processing steps

The choice data was supplied by Frank Milthorpe at Transport Data Centre, Transport for New South Wales. The choice, level-of-service and attraction data had already been processed into a format suitable for model estimation, and so unlike the Toronto data discussed in Section 3.2.3 there was no need to establish interim processing steps[4].

[4]Some of these interim processing steps were in fact setup by the author while working on these models for RAND Europe who developed the models on behalf of Transport Data Centre.

3.4 Comparison of Sydney and Toronto data

There are a number of differences between the Toronto and Sydney datasets that impact on the transferability analyses presented in subsequent chapters.

While the TTS data recorded trips made by all travel purposes, only the commute tours were available for this analysis. By contrast, tours for all purposes were available for the Sydney data. Therefore the analyses comparing the transferability of commute and non-commute travel presented in Chapters 5 and 6 were made using the Sydney data alone.

The Toronto data was also limited in terms of the socio-economic data recorded, and in particular by the omission on income from the survey. By contrast, the Sydney data collected incomes allowing income segmented models to be developed, and the Sydney data also recorded more socio-economic information allowing richer model specifications to be developed.

Only four modes have been modelled in the Toronto data, in part because the modes recorded varied between the different years and a set of modes common to all years was required for the transferability analysis, and in part because of a decision to omit park-and-ride trips from the analysis on the basis that the mode share for these trips did not justify the complexity of including them in the analysis. Seven models are represented in the Sydney data, the key difference is that train and bus are represented as separate modes, the other two additional modes of cycle and taxi account for just 1% of tours between them.

A key advantage of the Toronto data is that four separate years of data are available for analysis, allowing temporal transfers to be made for transfers ranging from 5 to 20 years. By contrast, only two years of Sydney data are available allowing only a 15 year transfer period. This means that the analysis of how transferability changes with transfer period presented in Chapters 5 and 6 have been undertaken using the Toronto data, and similarly the models that pooled data from different years that are presented in Chapter 7 have been developed using the Toronto data alone. The ability to make transfers over a long 20 year period was the reason that the Toronto data was used to make the random taste heterogeneity tests presented in Chapter 8.

Chapter 4

Model development

This chapter starts with a brief description of the software used for the model estimation work, before going to on describe the development of the nested logit models that have been used for the transferability analyses presented in Chapters 5 to 7. The work to develop models incorporating random taste heterogeneity is described later in Chapter 8.

Section 3.2 describes the Toronto data that was used to allow transferability analysis. It starts by describing the mode-destination choice data, goes on to describe the other data assembled including level of service data defining travel costs and times by the various modes modelled, and then concludes with a description of the commuter model specification that was developed for the transferability investigations.

Section 3.3 presents the corresponding information for the Sydney data, describing both the commute and home–other travel model specifications that were developed for the Sydney transferability analyses.

4.1 Software

The model estimation work was undertaken using the ALOGIT software[1]. The ALOGIT software was chosen because the author has more than a decade of experience in using the software, and because it is particularly well suited to estimating models with large numbers of alternatives such as mode-destination choice models, both in terms of data handling capabilities and in terms of speed. A further advantage is that one of the author's supervisors, Andrew Daly, is the author of the software, and his help proved particularly valuable when estimating models with randomly distributed parameters that pushed the software to its limits.

Some of the data processing prior to model estimation was undertaken using Microsoft Excel, and Excel was also used for analysis and interim tabulation of model results.

4.2 Toronto

4.2.1 Mode and destination alternatives

In order to make tests of model transferability, it was necessary to specify modal alternatives that could be defined by each year of the TTS survey included in the analysis. Specifying the modal alternatives was complicated by the fact that the transit modes recorded in the various TTS surveys have varied from year to year. Table 4.1 summarises the modes recorded for the home–work samples.

With the exception of 2001, transit has been split into local transit, subway with car access, GO-Rail with transit access and GO-Rail with car access. Local

[1] www.alogit.com.

Table 4.1: home–work mode shares by year of TTS survey

Mode	1986		1996		2001		2006	
car driver	34,211	65.6%	44,528	69.7%	55,966	70.5%	50,032	68.6%
car passenger	4,755	9.1%	5,853	9.2%	6,789	8.6%	5,775	7.9%
local transit	10,283	19.7%	9,230	14.5%	12,603	15.9%	10,604	14.5%
walk	1,155	2.2%	1,389	2.2%	808	1.0%	2,159	3.0%
Modelled	50,404	96.6%	61,000	95.5%	76,166	96.0%	68,570	94.1%
subway, car access	692	1.3%	741	1.2%			1190	1.6%
GO-Rail, transit access	426	0.8%	499	0.8%			111	0.2%
GO-Rail, car access	632	1.2%	1418	2.2%			2411	3.3%
transit, car access					3198	4.0%		
premium bus							151	0.2%
bike			207	0.3%			151	0.2%
Not modelled	1,750	3.4%	2,865	4.5%	3,198	4.0%	4,323	5.9%

transit can be modelled directly using Emme LOS, but for the other transit modes there is a need to model choice of access station, which results in a more complex treatment of LOS, with origin to access station and access station to destination legs represented separately. This results in a substantial increase in model run times, and given that these modes account for a relatively small percentage of the total data, and are defined differently in 2001, it was decided to exclude them from the modelling. It is noted that the 2001 local transit definition will include transit access to GO-Rail trips which are excluded in other years, which explains why the local transit share in 2001 is slightly higher than the 1996 and 2006 shares. Premium bus is only recorded in 2006, and accounts for just 0.2% of data, and has therefore been excluded. Finally, bike is only recorded separately in the 1996 and 2006 datasets, and has therefore been excluded from the modelling. However, in the 2001 data bike trips were recorded together with walk and so could not be excluded, and so the walk share presented for 2001 is actually for walk plus bike. This makes the low walk share in the 2001 data relative to the other years appear suspicious[2].

[2] The low walk share in the 2001 data has been discussed with Eric Miller who coordinated the supply of the TTS data. Eric agrees the share looks suspiciously low but does not have an explanation for why this is so. There are other areas where the 2001 data is also anomalous, for

The models included in the models are therefore car driver, car passenger, local transit and walk which account for at least 94% of observations in each year of TTS data. The availability conditions for these four modes were specified as follows:

- car driver (CD) is available if the individual has a licence and their household owns at least one car
- car passenger (CP) is available to all individuals
- local transit (LT) is available if there is a transit path with non-zero transit in-vehicle time between the origin and destination zone
- walk (WK) is available to all individuals

These availability conditions are consistent with those that have been used to develop mode choice models used by planning agencies in the study area (Miller, 2007), though Miller additionally imposes a 150 minute total travel time in one direction upper limit on local transit and a 3km upper limit on walk trips. The walk distance parameter in the model specifications tested means that upper limits are not required as availability conditions as longer tours have a lower probability of choice.

Destination alternatives are available if there is at least one job in the destination zone. Setting alternatives that are rarely or never chosen to be unavailable is expected to yield better parameter estimates. Furthermore, the availability conditions should improve model transferability because they provide a mechanism for taking account of future changes. For example, growth in licence holding and car ownership over time would be expected to result in increases in the car driver share *ceteris paribus*.

The size variable in the models is total employment. Total employment is used

example the high fraction of zones with non-zero parking costs highlighted in Table 3.6.

because the number of commuters travelling to a zone is expected to be directly proportional to the number of jobs in that zone.

4.2.2 Model specification

The model specification and associated estimation code was developed by the author alone. However, the basic design of the model draws heavily on standard RAND Europe modelling practice summarised in Fox et al. (2003).

The model specifications used to make the transferability tests were developed by making a series of tests to develop model specifications that best explained the mode-destination choices observed in the 1986 TTS data. Parody (1977), Train (1978) and Badoe and Miller (1995a) all demonstrated that the temporal transferability of mode choice models improves with model specification. To investigate whether this finding holds for models of mode-destination choice, and to facilitate analysis of changes in cost sensitivity over time, three model specifications have been developed:

- 'sparse' – linear and log cost terms, level of service terms, and mode and destination constants
- 'car avail' – sparse specification plus car availability terms
- 'detailed' – car avail specification plus socio-economic terms

Fox et al. (2009) found that estimating separate linear and log cost terms could yield a significant improvement in model fit relative to linear-only and log-only cost specifications. Furthermore, this specification can yield more plausible elasticities than a pure log-cost formulation which usually gives a better fit than a pure linear-cost formulation, but has the disadvantage of giving low kilometrage elasticities[3]. Therefore separate linear and log cost terms were tested on the TTS data, and were found to be significant in all three specifications.

Daly and Carrasco (2009) suggested that the influence of the log cost term, which gives rise to an increase in value of time with distance, is in part as a result of significant heterogeneity of preference leading to self-selection, so that value of time does not necessarily increase with distance at an individual level. They presented empirical analysis in support of this hypothesis in their paper, and this issue is discussed in more detail in Chapter 9.

No intrazonal tours, i.e. tours where the origin and destination zones are the same, were included in the sample of home–work tours used for model estimation and therefore intrazonal destinations were set to be unavailable. As discussed in section 2.1.1, in a multinomial model the IIA property means that consistent estimates of the model parameters can be obtained from a sub-set of the model alternatives. However, as discussed below the final model specifications are not multinomial and therefore the consistency condition does not strictly hold.

Two alternative model structures were tested, destinations above modes, and modes above destinations. In the modes above destinations structure, the structural parameter was significantly greater than one (1.18 with a t-ratio relative to a value of 1 of 8.4) and therefore the structure could be rejected. For the destinations above modes structure, the structural parameter was significantly lower than one, and therefore this structure was adopted.

Only a single PT mode has been modelled, and therefore it was not possible to test a structure with a PT nest (in models with a number of PT modes, the public transport models are often placed in a nest as these modes are closer substitutes than non-PT modes). A car nest was tested to investigate whether

[3] In a pure log-cost formulation, a uniform percentage increase to the cost of each destination results in the utility of each destination increasing by the same amount, and therefore no destination choice response is observed in an elasticity test.

car driver and car passenger are closer substitutes than the other modes, but the nest parameter was significantly greater than one and therefore the structure was rejected to guarantee consistency with utility maximisation. Thus in the final model structure the four modal alternatives are at the same level in the choice structure.

The final model specifications are defined in Table 4.2. On the left hand side of the table, the different model parameters β are defined. The columns for each mode define the data items x that each of the model parameters are multiplied by. For constant terms, the x values are simply 1 indicating that the constant is applied to that mode. The relatively small number of socio-economic terms added in the detailed specification reflects the fact that just two socio-economic variables, age and gender, were included on the estimation files. All costs are in cents and all times are in minutes.

The age bands used on the estimation file supplied for the 2001 TTS data differ to those used for the other survey years. As a result, the age terms identified in the detailed specification cannot be defined using the 2001 estimation file, and so the detailed specification cannot be estimated on, or transferred to, the 2001 data.

4.2.3 Utility functions

The final Toronto model uses a destinations and modes structure. The mode-destination utilities $V_{m'd}$ for the detailed model specification that enter into Equation 2.15 are defined in Table 4.3. The size functions $S_{d'}$ that enter into Equation 2.14 at the destination level in the structure are defined separately.

where: $Auto\_Cost(d)$ is the car cost to destination d in cents
$Auto\_Time(d)$ is the travel time to destination d in minutes

Table 4.2: Toronto model specifications

Parameter		Car driver	Car pass.	Local transit	Walk
Attraction term					
TotEmp	jobs	jobs	jobs	jobs	jobs
Cost terms					
Cost	linear cost	car cost		LT fare	
LogCost	log cost	ln(car cost)		ln(LT fare)	
LOS terms					
CarTime	car IVT	IVT	IVT		
TranIVT	transit IVT			IVT	
TranWait	transit wait time			wait time	
TranWalk	transit walk time			walk time	
APDist	car pass. distance		distance		
WalkDist	walk distance				distance
Destination terms					
CBDDest	CBD destination	1	1	1	1
CBDLT	CBD destination			1	
Mode constants					
AP	car passenger		1		
LT	local transit			1	
WK	walk				1
Car availability (car avail and detailed spec.s only)					
AD2pVeh	2+ vehicles	1			
AP1Veh	1 vehicle		1		
AP2pVeh	2+ vehicles		1		
Socio-economics (detailed spec. only)					
ADAge1617	aged 16 to 17	1			
ADAge1825	aged 18 to 25	1			
ADAge2630	aged 26 to 30	1			
ADMale	male	1			
WkMale	male				1

where: LT denotes local transit, IVT denotes in-vehicle time

$CBD(d)$ is 1 if destination d is located in the CBD, 0 otherwise

$NVeh$ is the number of vehicles owned by the household

$female$ is 1 is the individual is female, 0 otherwise

age is the age of the individual in years

$Hway\_Dist(d)$ is the highway distance to destination d in kilometres

Table 4.3: Toronto detailed model specification utility functions

Mode	Parameter β	Variable X	Variable type
Car driver	Cost	Auto_Cost(d)	cost
	LogCost	log(max(Auto_Cost(d), 1))	cost
	AutoTime	Auto_Time(d)	level-of-service
	CBDDest	CBD(d)	constant
	AD2pVeh	ifge(Nveh, 2)	socio-economic
	ADmale	ifeq(female, 0)	socio-economic
	ADage1617	ifin(age, 16,17)	socio-economic
	ADage1825	ifin(age, 18,25)	socio-economic
	ADage2630	ifin(age, 26,30)	socio-economic
Car passenger	AP		constant
	AutoTime	Auto_Time(d)	level-of-service
	APDist	Hway_Dist(d)	level-of-service
	CBDDest	CBD(d)	constant
	AP1Veh	ifeq(Nveh, 1)	socio-economic
	AP2pVeh	ifge(Nveh, 2)	socio-economic
Local transit	LT		constant
	Cost	Tran_Fare(d)	cost
	LogCost	log(max(Tran_Fare(d), 1))	cost
	TranIVT	Tran_IVT(d)	level-of-service
	TranWalk	Tran_Walk(d)	level-of-service
	TranWait	Tran_Wait(d)	level-of-service
	CBDDest	CBD(d)	constant
	CBDLT	CBD(d)	constant
Walk	Wk		constant
	WalkDist	Hway_Dist(d)	level-of-service
	CBDDest	CBD(d)	constant
	WkMale	ifeq(female, 0)	socio-economic

$Tran\_Fare(d)$ is the transit fare to destination d in cents

$Tran\_IVT(d)$ is the transit in-vehicle time to destination d in minutes

$Tran\_Walk(d)$ is the transit walk time to destination d in minutes

$Tran\_Wait(d)$ is the transit wait time to destination d in minutes

4.2.4 Model results

The model results for the detailed model specification are given in Table 4.4. In Table 4.4, in each column the parameter value β is presented on the left and the t-ratio for the parameter is presented on the right. The t-ratio is given by the ratio β/σ where σ is the standard deviation of the parameter estimate. For model parameters, the t-ratios define the significance of the parameter relative to a value of zero. For the structural parameters and the scale parameters the t-ratios have been presented relative to a value of one.

All costs in the models are defined in 1986 prices and furthermore adjustments have been applied to account for real growth in incomes relative to 1986 values. Furthermore the parameters have been adjusted to take account of scale differences between the different years of data. These procedures are described in detail in Section 5.1 and 5.2 respectively.

Model results for the 'sparse' and 'car avail' model specifications are presented in Appendix B.

Table 4.4: Home–work model results, detailed model specification

	HW_MD_1986_C		HW_MD_1996_C_DX		HW_MD_2006_C	
Log-likelihood		-306,365.0		-365,942.4		-411,833.4
Observations		50,254		60,241		64,959
LL per obs		-6.096		-6.075		-6.340
Cost parameters						
LogCost	-0.358	-22.9	-0.595	-32.8	-0.335	-16.3
Cost	-0.0011	-12.5	-0.0006	-7.7	-0.0016	-20.1
Level of service						
CarTime	-0.042	-42.5	-0.038	-41.7	-0.044	-37.2
TranIVT	-0.028	-40.5	-0.029	-38.2	-0.025	-35.5
TranWait	-0.059	-22.5	-0.051	-29.3	-0.052	-25.6
TranWalk	-0.027	-15.9	-0.029	-11.1	-0.026	-17.7
APDist	-0.022	-27.4	-0.026	-33.4	-0.030	-35.2
WalkDist	-0.621	-44.0	-0.712	-46.8	-0.622	-50.3
Destination terms						
CBDDest	0.518	15.2	0.663	18.2	-0.135	-4.5
CBDLT	0.143	3.6	0.171	3.8	1.014	23.4
Mode constants						
AP	-4.317	-43.2	-5.573	-50.8	-4.109	-38.9
LT	1.023	20.3	1.579	22.7	1.054	20.0
Wk	0.125	1.3	-0.159	-1.5	0.833	8.6
Structural parameter						
TR_D_M	0.815	56.4	0.782	56.2	0.785	49.5
Car availability						
AD2pVeh	1.321	41.8	1.650	42.0	1.700	47.3
AP1Veh	1.580	21.8	1.831	25.2	1.682	23.4
AP2pVeh	2.019	27.1	2.315	29.8	2.173	28.8
Socio economics						
ADAge1617	-2.173	-6.4	-4.069	-4.9	-3.241	-5.7
ADAge1825	-0.872	-25.2	-1.084	-22.5	-1.463	-32.3
ADAge2630	-0.177	-5.0	-0.243	-6.0	-0.383	-8.5
ADMale	1.024	37.8	1.175	38.6	0.924	33.0
WkMale	0.275	4.1	0.157	2.1	0.159	2.5
Attraction term						
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a

4.3 Sydney

4.3.1 Mode and destination alternatives

With the exception of two commmute tours made by air and one by monorail, and four other travel tours made by air and two by monorail, all of the modes recorded in the STM data were modelled. Table 4.5 summarises the mode shares for the home–work samples.

Table 4.5: Sydney home–work mode shares by year

Mode	1991		2006	
car driver	3,231	63.2%	3,369	65.1%
car passenger	473	9.3%	328	6.3%
train	762	14.9%	734	14.2%
bus	318	6.2%	415	8.0%
cycle	31	0.6%	32	0.6%
walk	275	5.4%	276	5.3%
taxi	21	0.4%	19	0.4%
Total	5,111	100.0%	5,173	100.0%
Occupancy		1.146		1.097

A modest increase in car driver share is observed between 1991 and 2006, but the big change is the large reduction in the car passenger share and the consequent reduction in mean occupancy. The bus share has also increased. These changes are consistent with those observed by Xu and Milthorpe (2010) who analysed changes in the Census Journey to Work data over the 1981 to 2011 period, and including analysis of the 1991 and 2006 datasets.

Table 4.6 summarises the mode shares for the home–other travel samples.

The car driver share has increased at the expense of car passenger, train and bus. The walk share has also increased slightly.

Table 4.6: Sydney home–other travel mode shares by year

Mode	1991		2006	
car driver	4,647	43.7%	4,918	47.0%
car passenger	3,455	32.5%	3,123	29.8%
train	218	2.0%	176	1.7%
bus	272	2.6%	180	1.7%
cycle	111	1.0%	100	1.0%
walk	1,892	17.8%	1,936	18.5%
taxi	49	0.5%	31	0.3%
Total	10,644	100.0%	10,464	100.0%
Occupancy		1.743		1.635

For home–other travel, transferability tests were also undertaken for three sub-purposes that collectively sum to total home–other travel:

- serve passenger (travel to pick up or drop up another individual)
- personal business
- leisure (specifically social visits, recreation, entertainment, sport, holiday)

Table 4.7 presents the mode shares by year for these three sub-purposes.

Table 4.7: Sydney home–other travel sub-purpose mode shares by year

Mode	Serve passenger		Personal business		Leisure	
	1991	2006	1991	2006	1991	2006
car driver	48.9%	55.9%	53.6%	57.5%	37.5%	38.0%
car pass.	36.0%	31.5%	19.0%	19.6%	34.0%	31.6%
train	0.3%	0.4%	3.3%	3.0%	2.8%	2.2%
bus	1.1%	0.3%	5.1%	3.8%	2.8%	2.1%
bike	0.0%	0.0%	0.5%	0.7%	1.8%	1.5%
walk	13.6%	11.8%	17.9%	14.7%	20.4%	24.2%
taxi	0.1%	0.1%	0.6%	0.7%	0.6%	0.3%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

It can be seen from Table 4.7 that the mode shares vary across the three sub-purposes, with car driver usage highest for personal business, but car passenger use highest for serve passenger and leisure, and with very little public transport usage for serve passenger travel. Furthermore, the changes in mode share vary between the sub-purposes, in particular for serve passenger and personal business the car driver share has increased and the walk share has reduced, whereas for leisure there has been little change in the car driver share and an increase in the walk share.

The availability conditions for the seven modelled modes were specified as follows:

- car driver (CD) is available if the individual has a licence and their household owns at least one car
- car passenger (CP) is available to all individuals
- train (TR) is available if there is a path in the PT assignment with non-zero train in-vehicle time between the origin and destination zone
- bus (BS) is available if there is a path in the bus-only assignment with non-zero bus in-vehicle time between the origin and destination zone
- cycle (CY) is available to all individuals
- walk (WK) is available to all individuals
- taxi (TX) is available to all individuals

Destination alternatives are available in the home–work model if there is at least one job in the destination zone, and available in the home–other travel model if the population is at least one in the destination zone.

Total employment was used as the size variable in the home–work model as the number of individuals commuting to each zone is expected to be proportional to the number of jobs in that zone. For home–other travel, drawing on earlier modelling work in Sydney (Fox et al., 2003), multiple size variables were tested to reflect the heterogenous nature of home–other travel. Population was used to represent the attractiveness of destinations for sub-purposes like serve passenger and visiting friends, whereas service employment was used to reflect personal business travel.

4.3.2 Model specification

The model specification and associated estimation code took as its starting point existing ALOGIT code that RAND Europe had developed over a number of years on behalf of the Bureau of Transport Statistics, Transport for New South Wales. The author modified the code so that identical model specifications were used for each year of data. Furthermore, for home–other travel the author created sub-purpose models by filtering the data by sub-purpose.

Consistent with the Toronto specifications described in Section 4.2.2, a number of model specifications have been tested to investigate whether transferability increases as models specification improves:

- 'sparse' – linear and log cost terms, level of service terms and constants
- 'car avail' – sparse specification plus car availability terms
- 'detailed' – car avail specification plus socio-economic terms
- 'detailed & income' – detailed specification but with cost sensitivity segmented by income

The home–other sub-purpose models were developed using the 'detailed' specification (i.e. the cost sensitivity terms were not segmented by income) after initial tests found that the income segmented cost terms were not significantly better than a single cost term for all of the sub-purposes.

No LOS was available for PT for intrazonals (i.e. tours with the same origin and destination zone) and as few PT intrazonals were observed in the data PT modes were set to be unavailable for intrazonals. For the other modes which use highway LOS, intrazonals are more frequently observed (particularly for walk), but once again no level of service was available from the Emme skims. Therefore intrazonal LOS was imputed using a 'nearest neighbour' whereby the nearest zone by distance on the highway network was identified, and then half of the travel time and distance to this done was used to calculate the intrazonal LOS.

Two alternative model structures were tested for home–work travel, destinations above modes, and modes above destinations. In the destinations above modes structure, the structural parameter was significantly greater than one (1.13 with a t-ratio compared to a value of 1 of 2.7) and therefore the structure could be rejected. For the modes above destinations structure, the structural parameter was significantly lower than one, and therefore this structure was adopted. It is noteworthy that this is the opposite structure to that identified from the analysis of the Toronto data despite the fact that the car driver and public transport shares for home–work travel are similar in the two contexts. This result suggests that mode-destination model structures are not spatially transferable.

Similar tests were undertaken for home–other travel and again the modes above destinations structure was accepted, but the reverse destinations above modes structure was rejected.

The final home–work and home–other travel model specifications are defined in Table 4.8 and Table 4.9. Note that due to space limitations the separate cost parameters used by income group in the 'detailed & income' specification are not presented; however these are detailed in the utility functions presented in Section 4.3.3. On the left hand side of the table, the different model parameters β are defined. The columns for each mode define the data items x that each of the model parameters are multiplied by. For constant terms, the x values are simply 1 indicating that the constant is applied to that mode. Car competition is defined as a household where the number of licence holders exceeds the number of vehicles owned. The passenger opportunity term is applied if the household owns at least one car and there is at least one other individual in the household who owns a licence. All costs are in cents and all times are in minutes.

Table 4.8: Sydney home–work model specifications

Parameter		CD	CP	TR	BS	BK	WK	TX
Attraction term								
TotEmp	jobs	jobs	jobs	jobs	jobs	jobs	jobs	jobs
Cost terms								
Cost	linear cost	car cost	car cost	train fare	bus fare			taxi fare
LogCost	log cost	ln(car cost)	ln(car cost)	ln(train fare)	ln(bus fare)			ln(taxi fare)
LOS terms								
CarTime	car IVT	IVT	IVT					IVT
RlTime	rail IVT			IVT				
BusTime	bus IVT			IVT	IVT			
AccTime	PT access time			access time	access time			
FrWtTime	first wait time			wait time	wait time			
OtWtTime	other wait time			wait time	wait time			
CarPDist	distance		distance					
BkDist	distance					distance		
WalkDist	distance						distance	
Destination terms								
Intra	intrazonal	1	1			1	1	1
CBDDest	CBD destination	1	1	1	1	1	1	1
CBDRail	CBD destination			1				
CBDBus	CBD destination				1			
Mode constants								
CrP	car passenger		1					
Trn	train			1				
Bus	train				1			
Bk	bike					1		
Wk	walk						1	
Tx	taxi							1
Car availability (car avail and detailed spec.s only)								
CarComp	car competition	1						
CmpCrDr	company car(s)		1					
PassOpts	passenger opportunity		1					
Socio-economics (detailed spec.s only)								
MaleCrDr	male	1						
Ageu24CrD	aged under 25	1						
HiPersInc	income $26k+ p.a.			1				
FullTmRl	full-time worker			1				
MaleBk	male						1	

where: IVT denotes in-vehicle time, ln is the natural logarithm

Table 4.9: Sydney home–other travel model specifications

Parameter		CD	CP	TR	BS	BK	WK	TX
Attraction term								
TotEmp	jobs	jobs	jobs	jobs	jobs	jobs	jobs	jobs
Cost terms								
LogCost	log cost	ln(car cost)	ln(car cost)	ln(train fare)	ln(bus fare)			ln(taxi fare)
LOS terms								
CarTime	car IVT	IVT	IVT					IVT
RlTime	rail IVT			IVT				
BusTime	bus IVT			IVT	IVT			
AccTime	PT access time			access time	access time			
WaitTime	first wait time			wait time	wait time			
CarPDist	distance		distance					
BkDist	distance					distance		
WalkDist	distance						distance	
Destination terms								
Intra	intrazonal	1	1			1	1	1
CBDDest	CBD destination	1	1	1	1	1	1	1
CBDRail	CBD destination			1				
CBDBus	CBD destination				1			
Mode constants								
CrP	car passenger		1					
Trn	train			1				
Bus	train				1			
Bk	bike					1		
Wk	walk						1	
Tx	taxi							1
Car availability (car avail and detailed spec.s only)								
CarComp	car competition	1						
PassOpts	passenger opportunity		1					
Socio-economics (detailed spec.s only)								
CarPMale	male		1					
BusMale	male				1			
BikeMale	male					1		
CarPu10	aged under 10		1					
CarP60pl	aged 60+		1					
PT10to19	aged 10–19			1	1			
PT60pl	aged 60+			1	1			

where: IVT denotes in-vehicle time, ln is the natural logarithm

4.3.3 Utility functions

The utility functions used in the detailed & income specification of the home–work model are detailed in Table 4.10.

Table 4.10: Sydney home–work detailed & income model specification utility functions

Mode	Parameter β	Variable X	Variable type
Car driver	TotEmp	LogEmp(d)	attraction
	Cost1	CDfact * car_cst_NT(d) * ifeq(incb, 1)	cost
	Cost2	CDfact * car_cst_NT(d) * ifeq(incb, 2)	cost
	Cost3	CDfact * car_cst_NT(d) * ifeq(incb, 3)	cost
	LogCost	log(max(CDfact*car_cst_NT(d), min_cost))	cost
	CarTime	Car_Tm_Nt(d)	level-of-service
	CBDDest	CBD(d)	constant
	Intra	IZ(d)	constant
	CarComp	ifgt(hhld_fplic, hhcars+ccars)	socio-economic
	CmpCrDr	ifge(ccars, 1)	socio-economic
	MaleCrDr	ifeq(gender, 1)	socio-economic
	Ageu24CrD	ifle(age, 24)	socio-economic
Car passenger	CrP		constant
	TotEmp	LogEmp(d)	attraction
	Cost1	CPfact * car_cst_NT(d) * ifeq(incb, 1)	cost
	Cost2	CPfact * car_cst_NT(d) * ifeq(incb, 2)	cost
	Cost3	CPfact * car_cst_NT(d) * ifeq(incb, 3)	cost
	LogCost	log(max(CPfact*car_cst_NT(d), min_cost))	cost
	CarTime	Car_Tm_Nt(d)	level-of-service
	CarPDist	Car_Ds_Nt(d)	level-of-service
	Intra	IZ(d)	constant
	CBDDest	CBD(d)	constant
	PassOpts	ifge(hhcars+ccars, 1) * ifgt(hhld_fplic, fullp_lic)	socio-economic

Table 4.11: Sydney home–work detailed & income model specification utility functions (continued)

Mode	Parameter β	Variable X	Variable type
Train	Trn		constant
	TotEmp	LogEmp(d)	attraction
	Cost1	Rail_fare(d) * ifeq(incb, 1)	cost
	Cost2	Rail_fare(d) * ifeq(incb, 2)	cost
	Cost3	Rail_fare(d) * ifeq(incb, 3)	cost
	LogCost	log(max(Rail_fare(d), min_cost))	cost
	RlTime	Rail_IVT(d)	level-of-service
	BusTime	TBus_IVT(d)	level-of-service
	AccTime	Rail_walkT(d)	level-of-service
	FrWtTm	Rail_fwait(d)	level-of-service
	OrWtTme	Rail_owait(d)	level-of-service
	CBDDest	CBD(d)	constant
	CBDRail	CBD(d)	constant
	HiPersInc	ifge(incb, 3)	socio-economic
	FullTmRl	ifeq(adult_st, 3)	socio-economic
Bus	Bus		constant
	TotEmp	LogEmp(d)	attraction
	Cost1	Bus_fare(d) * ifeq(incb, 1)	cost
	Cost2	Bus_fare(d) * ifeq(incb, 2)	cost
	Cost3	Bus_fare(d) * ifeq(incb, 3)	cost
	LogCost	log(max(Bus_fare(d), min_cost))	cost
	BusTime	Bus_IVT(d)	level-of-service
	AccTime	Bus_walkT(d)	level-of-service
	FrWtTm	Bus_fwait(d)	level-of-service
	OrWtTme	Bus_owait(d)	level-of-service
	CBDDest	CBD(d)	constant
	CBDBus	CBD(d)	constant
Bike	Bk		constant
	TotEmp	LogEmp(d)	attraction
	BkDist	slow_dist(d)	level-of-service
	Intra	IZ(d)	constant
	CBDDest	CBD(d)	constant
	MaleBike	ifeq(gender, 1)	socio-economic
Walk	Wk		constant
	TotEmp	LogEmp(d)	attraction
	WkDist	slow_dist(d)	level-of-service
	Intra	IZ(d)	constant
	CBDDest	CBD(d)	constant
Taxi	Tx		constant
	TotEmp	LogEmp(d)	attraction
	CarTime	Car_Tm_Nt(d)	level-of-service
	Cost1	tx_cst(d) * ifeq(incb, 1)	cost
	Cost2	tx_cst(d) * ifeq(incb, 2)	cost
	Cost3	tx_cst(d) * ifeq(incb, 3)	cost
	LogCost	log(max(tx_cst(d), min_cost))	cost
	CBDDest	CBD(d)	constant

where: $LogEmp(d)$ is the log of total employment in destination d

$CDfact$ is the proportion of the total car cost allocated to car driver

$car\_cst\_NT(d)$ is the car cost to destination d in cents

$incb$ is the income band (1: under \$15.6k, 2: \$15.6–26k, 3: \$26–36.4k+)

$Car\_Tm\_Nt(d)$ is the car time to destination d in minutes

$CBD(d)$ is 1 if destination d is located in the CBD, 0 otherwise

$IZ(d)$ is 1 if destination d is an intrazonal, 0 otherwise

$hhld\_fplic$ is the number of licence holders in the household

$hhcars$ is the number of privately owned cars available to the household

$ccars$ is the number of company owned available to the household

$gender$ is 1 is the individual is male, 0 otherwise

age is the age of the individual in years

$CPfact$ is the proportion of the total car cost allocated to car passenger

$Car\_Ds\_Nt(d)$ is the highway distance to destination d in kilometres

$Rail\_fare(d)$ is the train fare to destination d in cents

$Rail\_IVT(d)$ is the train in-vehicle time to destination d in minutes

$TBus\_IVT(d)$ is the bus access time for train to destination d in minutes

$Rail\_Walk(d)$ is the walk access time for train to destination d in minutes

$Rail\_fwait(d)$ is the first wait time for train to destination d in minutes

$Rail\_owait(d)$ is the other wait time for train to destination d in minutes

$adult\_st$ is the adult status code of the individual

$Bus\_fare(d)$ is the bus fare to destination d in cents

$Bus\_IVT(d)$ is the bus in-vehicle time to destination d in minutes

$Bus\_walkT(d)$ is the walk access time for bus to destination d in minutes

$Bus\_fwait(d)$ is the first wait time for bus to destination d in minutes

$Bus\_owait(d)$ is the other wait time for bus to destination d in minutes

$slow_dist(d)$ is the off-peak highway distance to destination d in kilometres

$tx\_cst(d)$ is the taxi cost to destination d in cents

The utility functions used in the detailed & income specification of the home–other travel model are detailed in Table 4.12.

Table 4.12: Sydney home–other travel detailed & income model specification utility functions

Mode	Parameter β	Variable X	Variable type
Car driver	CarTime	Car_Tm_Nt(d)	level-of-service
	LogCost20	log(max(CDfact*car_cst_NT(d), min_cost)) * ifeq(pinc_band, 1)	cost
	LogCost2050	log(max(CDfact*car_cst_NT(d), min_cost)) * ifeq(pinc_band, 2)	cost
	LogCost50pl	log(max(CDfact*car_cst_NT(d), min_cost)) * ifeq(pinc_band, 3)	cost
	CBDDest	CBD(d)	constant
	Intra	IZ(d)	constant
	CarComp	ifgt(hhld_fplic, hhcars+ccars)	socio-economic
Car passenger	CrP		constant
	LogCost20	log(max(CPfact*car_cst_NT(d), min_cost)) * ifeq(pinc_band, 1)	cost
	LogCost2050	log(max(CPfact*car_cst_NT(d), min_cost)) * ifeq(pinc_band, 2)	cost
	LogCost50pl	log(max(CPfact*car_cst_NT(d), min_cost)) * ifeq(pinc_band, 3)	cost
	CarTime	Car_Tm_Nt(d)	level-of-service
	CarPDist	Car_Ds_Nt(d)	level-of-service
	Intra	IZ(d)	constant
	CBDDest	CBD(d)	constant
	PassOpts	ifge(hhcars+ccars, 1) * ifgt(hhld_fplic, fullp_lic)	socio-economic
	CarPMale	ifeq(gender, 1)	socio-economic
	CarPu10	iflt(age, 10)	socio-economic
	CarP60pl	ifge(age, 60)	socio-economic

Table 4.13: Sydney home–other travel detailed & income model specification utility functions (continued)

Mode	Parameter β	Variable X	Variable type
Train	Trn		constant
	LogCst20	log(max(Rail_fare(d), min_cost)) * ifeq(pinc_band, 1))	cost
	LogCst2050	log(max(Rail_fare(d), min_cost)) * ifeq(pinc_band, 2))	cost
	LogCst50pl	log(max(Rail_fare(d), min_cost)) * ifeq(pinc_band, 3))	cost
	RlTime	Rail_IVT(d)	level-of-service
	BusTime	TBus_IVT(d)	level-of-service
	AccTime	Rail_walkT(d)	level-of-service
	FrWtTm	Rail_fwait(d)	level-of-service
	OrWtTme	Rail_owait(d)	level-of-service
	CBDDest	CBD(d)	constant
	CBDRail	CBD(d)	constant
	PT10to19	ifin(age, 10,19)	socio-economic
	PT60pl	ifge(age, 60)	socio-economic
Bus	Bus		constant
	LogCst20	log(max(bus_fare(d), min_cost)) * ifeq(pinc_band, 1)	cost
	LogCst2050	log(max(bus_fare(d), min_cost)) * ifeq(pinc_band, 2)	cost
	LogCst50pl	log(max(bus_fare(d), min_cost)) * ifeq(pinc_band, 3)	cost
	LogCost	log(max(Bus_fare(d), min_cost))	cost
	BusTime	Bus_IVT(d)	level-of-service
	AccTime	Bus_walkT(d)	level-of-service
	WaitTime	Bus_fwait(d)	level-of-service
	WaitTime	Bus_owait(d)	level-of-service
	CBDDest	CBD(d)	constant
	CBDBus	CBD(d)	constant
	BusMale	ifeq(gender, 1)	socio-economic
	PT10to19	ifin(age, 10,19)	socio-economic
	PT60pl	ifge(age, 60)	socio-economic
Bike	Bk		constant
	BkDist	slow_dist(d)	level-of-service
	Intra	IZ(d)	constant
	CBDDest	CBD(d)	constant
	BikeMale	ifeq(gender, 1)	socio-economic
Walk	Wk		constant
	WkDist	slow_dist(d)	level-of-service
	Intra	IZ(d)	constant
	CBDDest	CBD(d)	constant
Taxi	Tx		constant
	CarTime	Car_Tm_Nt(d)	level-of-service
	LogCst20	log(max(tx_cst(d), min_cost)) * ifeq(pinc_band, 1)	cost
	LogCst2050	log(max(tx_cst(d), min_cost)) * ifeq(pinc_band, 2)	cost
	LogCst50pl	log(max(tx_cst(d), min_cost)) * ifeq(pinc_band, 3)	cost
	CBDDest	CBD(d)	constant

where: the variable definitions are as per the home–work, plus:

pinc_band is the personal income band (1: under \$20k, 2: \$20–50k, 3: \$50k+)

4.3.4 Model results

The model results for the 'detailed & income' model specifications are given in Table 4.14 for home–work, Table 4.15 for home–other travel and Table 4.16 for the home–other travel sub-purpose models.

In the results tables in each column the parameter value β is presented on the left and the t-ratio for the parameter is presented on the right. The t-ratio is given by the ratio β/σ where σ is the standard deviation of the parameter estimate. For model parameters, the t-ratios define the significance of the parameter relative to a value of zero. For the structural parameters and the scale parameters the t-ratios have been presented relative to a value of one. All cost parameters are presented in 1986 prices and values after applying the adjustment procedures described in Sections 5.1 and 5.2.

Model results for the 'sparse', 'car avail' and 'detailed' model specifications are presented in Appendix C.

Table 4.14: Sydney commute model results, detailed & income specification

	COM_D3_91		COM_D3_0408	
Log-likelihood		-29,507.5		-34,182.9
Observations		5,111		5,173
LL per obs		-5.773		-6.608
Cost parameters				
LogCost	-0.379	-9.1	-0.271	-7.2
Cost1	-0.0023	-10.7	-0.0023	-12.7
Cost2	-0.0018	-10.8	-0.0010	-9.4
Cost3	-0.0006	-5.2	-0.0003	-3.3
Level of service				
CarTime	-0.025	-27.0	-0.029	-35.3
RlTime	-0.010	-8.5	-0.012	-11.5
BusTime	-0.020	-12.3	-0.020	-14.8
AccTime	-0.026	-8.8	-0.011	-5.3
FrWtTm	-0.012	-1.7	-0.012	-2.5
OtWTme	-0.042	-7.8	-0.041	-9.6
CarPDist	-0.020	-7.8	-0.026	-7.2
BkDist	-0.164	-7.4	-0.160	-7.4
WlkDist	-0.598	-21.0	-0.601	-20.8
Destination terms				
Intra	-0.123	-1.4	0.265	2.3
CBDDest	-0.122	-1.3	-0.473	-5.7
CBDRail	0.865	6.4	1.392	11.8
CBDBus	0.454	2.7	1.293	9.7
Mode constants				
CrP	-6.053	-13.7	-4.312	-17.4
Trn	-3.076	-9.1	-1.473	-9.0
Bus	-2.495	-9.4	-1.637	-11.9
Bk	-10.667	-10.5	-6.515	-11.3
Wk	-2.044	-5.9	-0.424	-2.4
Tx	-5.977	-10.6	-4.696	-19.1
Car availability				
CarComp	-2.154	-13.1	-1.485	-19.4
CmpCrDr	0.872	5.9	0.690	7.1
PassOpts	1.850	5.9	1.546	6.5
Socio-economic				
Ageu24CrD	-0.872	-5.6	-0.382	-3.4
MaleCrDr	0.755	6.2	0.149	2.0
FullTmRl	1.302	5.5	0.014	0.1
HiPersInc	0.351	2.3	0.301	2.9
MaleBike	3.488	4.2	2.168	4.0
Attraction term				
TotEmp	1.000	n/a	1.000	n/a
Structural parameter				
TR_M_D	0.695	18.1	1.000	n/a

Table 4.15: Sydney home–other travel model results, detailed & income specification

	OTH_D3_91		OTH_D3_0408	
Log-likelihood		-46,922.1		-53,400.3
Observations		10,644		10,464
LL per obs		-4.408		-5.103
Cost parameters				
LogCst20	-1.169	-32.2	-0.700	-33.2
LogCst2050	-1.058	-26.2	-0.700	-33.2
LogCst50pl	-0.948	-13.0	-0.700	-33.2
Level of service				
CarTime	-0.053	-41.9	-0.066	-51.4
RlTime	-0.021	-7.9	-0.016	-7.5
BusTime	-0.023	-8.9	-0.029	-10.9
AccTime	-0.040	-7.5	-0.015	-4.2
WaitTime	-0.024	-4.2	-0.025	-5.2
CarPDist	0.007	4.5	0.014	8.0
BkDist	-0.332	-14.0	-0.319	-13.7
WlkDist	-0.740	-47.7	-0.927	-50.8
Destination terms				
Intra	-0.024	-0.5	-0.163	-4.0
CBDDest	-0.348	-2.6	-1.497	-10.9
CBDRail	0.893	3.6	1.707	7.1
CBDBus	0.453	1.8	1.199	4.1
Mode constants				
CrP	-11.204	-12.2	-6.347	-15.7
Trn	-10.630	-8.8	-5.911	-11.3
Bus	-9.226	-8.4	-5.329	-10.5
Bk	-20.509	-12.3	-11.373	-14.7
Wk	-6.565	-11.5	-2.271	-10.6
Tx	-14.144	-9.1	-8.583	-12.1
Car availability				
CarComp	-1.645	-7.3	-0.812	-7.1
PassOpts	5.519	10.1	2.762	11.2
Socio-economic				
CarPMale	-1.889	-8.3	-0.481	-4.6
BusMale	-1.394	-3.3	-0.274	-1.0
BikeMale	4.424	5.4	2.939	6.0
CarPu10	4.612	10.6	3.279	14.1
CarP60pl	1.086	4.1	0.518	3.8
PT10to19	-1.031	-2.2	-0.305	-1.1
PT60pl	3.465	7.8	0.881	3.8
Attraction term				
L_S_M	1.000	n/a	1.000	n/a
ServEmp	6.046	45.2	6.570	45.2
Structural parameter				
TR_M_D	0.399	18.3	0.594	11.2

Table 4.16: Sydney home–other travel sub-purpose model results, detailed specification

Model	OTH_C3_0408		OTH_C4_0408		OTH_C4_SP_0408		OTH_C4_PB_91		OTH_C4_OT_91	
Purposes	all data		sub-purp avail		serve passenger		personal business		other	
Log-likelihood	-53,403.0		-53,310.6		-16,267.8		-7,561.8		-28,745.9	
Observations	10,464		10,456		3,684		1,481		5,291	
D.O.F.	30		30		25		29		30	
Cost parameters										
LogCost	-0.700	-33.2	-0.940	-33.2	-1.084	-18.8	-0.880	-12.4	-0.767	-20.1
Level of service										
CarTime	-0.066	-51.4	-0.066	-51.5	-0.089	-29.7	-0.066	-21.8	-0.056	-35.3
RlTime	-0.016	-7.5	-0.016	-7.5	-0.032	-3.1	-0.024	-4.8	-0.013	-5.4
BusTime	-0.029	-10.9	-0.029	-10.8	-0.038	-2.8	-0.031	-6.0	-0.029	-9.0
AccTime	-0.015	-4.2	-0.014	-4.2	-0.026	-1.6	-0.020	-2.5	-0.012	-3.0
WaitTime	-0.025	-5.2	-0.025	-5.2	-0.058	-2.5	-0.036	-3.5	-0.019	-3.3
CarPDist	0.014	8.0	0.014	8.0	0.036	10.3	0.018	3.8	0.000	0.2
BkDist	-0.319	-13.7	-0.313	-13.1			-0.532	-4.2	-0.290	-12.2
WlkDist	-0.927	-50.8	-0.927	-50.8	-1.059	-25.2	-1.048	-17.4	-0.848	-39.5
Destination terms										
Intra	-0.163	-4.0	-0.164	-4.1	-0.538	-7.7	-0.123	-1.1	0.053	0.9
CBDDest	-1.497	-10.9	-1.495	-10.8	-1.256	-4.8	-1.620	-5.4	-1.389	-8.0
CBDRail	1.707	7.1	1.705	7.1			1.904	4.1	1.746	5.7
CBDBus	1.199	4.1	1.198	4.1					1.230	3.5
Mode constants										
CrP	-6.347	-15.7	-6.337	-15.8	-8.115	-8.4	-6.184	-7.4	-5.191	-10.3
Trn	-5.911	-11.3	-5.971	-11.4	-5.449	-4.0	-3.679	-4.3	-6.022	-8.3
Bus	-5.329	-10.5	-5.498	-10.9	-6.788	-5.0	-3.218	-4.0	-5.260	-7.5
Bk	-11.373	-14.7	-11.138	-14.6			-10.197	-5.7	-10.538	-10.2
Wk	-2.271	-10.6	-2.476	-11.4	-3.926	-7.2	-2.483	-4.6	-1.211	-4.8
Tx	-8.583	-12.1	-8.575	-12.1	-8.683	-5.9	-6.691	-5.8	-9.565	-8.8
Car availability										
CarComp	-0.812	-7.1	-0.815	-7.1	-0.426	-2.0	-1.102	-3.9	-1.094	-6.0
PassOpts	2.762	11.2	2.760	11.2	3.206	6.0	2.715	5.2	2.728	7.9
Socio-economic										
CarPMale	-0.481	-4.6	-0.485	-4.7	-0.031	-0.2	-0.692	-2.6	-0.824	-5.2
BusMale	-0.274	-1.0	-0.270	-1.0	0.517	0.6	-0.251	-0.6	-0.567	-1.5
BikeMale	2.939	6.0	2.882	5.7			2.503	2.0	3.074	4.9
CarP¡10	3.279	14.1	3.244	14.1	2.531	7.3	3.151	4.4	3.635	9.8
CarP60pl	0.518	3.8	0.515	3.8	0.747	2.3	0.389	1.4	0.044	0.2
PT10to19	-0.305	-1.1	-0.326	-1.1	-0.983	-0.9	-0.532	-1.0	-0.355	-0.9
PT60pl	0.881	3.8	0.800	3.5	1.566	2.2	-0.437	-1.2	0.640	2.1
Attraction term										
L_S_M	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a
ServEmp	6.570	45.2	6.565	45.2	7.837	29.8	22.317	20.4	4.041	23.0
Structural parameter										
TR_M_D	0.581	11.8	0.581	11.7	0.680	3.9	0.647	4.2	0.524	10.2

Chapter 5

Parameter transferability

This chapter presents analysis of changes in model parameters over time that has been undertaken using both the Toronto and Sydney datasets.

The Chapter starts in Section 5.1 by considering how to take account of changes in cost sensitivity that result from real income growth over time. This analysis is presented first because the analysis presented in subsequent sections of this chapter, and the analysis described in subsequent chapters, incorporates the approach for adjusting for real income growth discussed in Section 5.1. Next, section 5.2 briefly details how adjustments have been applied to take account of scale differences – i.e. differences in the level of unexplained error – between different years of data.

The analysis of parameter transferability is split into three sections. In Section 5.3, analysis of the significance of parameter differences in presented. Section 5.4 documents analysis of changes in the changes in parameter magnitude. Finally, Section 5.6 focuses on the transferability of the structural parameters that capture the relative levels of error in mode and destination choice.

The thinking in Section 5.1.1 was informed by the literature review presented in Daly and Fox (2012). Earlier results from the analyses presented in Sections 5.2 and 5.4 were presented in Fox et al. (2014).

5.1 Changes in cost sensitivity over time

5.1.1 Adjusting for real income growth

In Daly and Fox (2012), the literature on the longitudinal elasticity of VOT to real income growth over time was reviewed. The conclusion from this review was that longitudinal income elasticities are around 1. A key piece of UK evidence is the meta-analysis work undertaken by Mark Wardman and others which has fed into the UK Department for Transport's web-based guidance (named 'WebTAG'). The most recent set of this UK analysis identified a GDP/capita elasticity of 0.9 (Abrantes and Wardman, 2011). Subsequently Börjesson (2014) found that significant reduction in the magnitude of the cost parameter for 1994 and 2007 Swedish value of time data models could be entirely explained by adjusting for real income growth over the period, i.e. that the longitudinal income elasticity for her Swedish values of time data was 1.

Drawing on this evidence, model tests were undertaken where adjustments were made to the cost parameters to take account of real income growth measured using GDP/capita (i.e. using a longitudinal elasticity of 1). The results of model transfers where costs were adjusted in this way were then compared to the fit in the transfer context of models where no adjustment to the cost parameters was made.

The real income growth adjustment is applied to satisfy Equation 5.1.

$$VOT_t = G.VOT_b \tag{5.1}$$

where: VOT_t is the VOT in the transfer context t
VOT_b is the VOT in the base context b
G is the real income growth adjustment

In the base context, VOT in a model with both linear and log cost parameters is given by Equation 5.2.

$$VOT_b = \frac{\partial U / \partial time}{\partial U / \partial cost} = \frac{\beta_{Time}}{\beta_{Cost} + \frac{\beta_{LogCost}}{cost}} \tag{5.2}$$

where: β_{Time} is the travel time parameter
β_{Cost} is the linear cost parameter
$\beta_{LogCost}$ is the log cost parameter
$cost$ is the modelled cost

The utility functions for the Toronto and Sydney models which include β_{Time}, β_{Cost} and $\beta_{LogCost}$ parameters are defined in Sections 4.2.3 and 4.3.3.

Combining Equations 5.1 and 5.2, VOT in the transfer context is then given by Equation 5.3.

$$VOT_t = G.VOT_b = \frac{\beta_{Time}}{\frac{1}{G}(\beta_{Cost} + \frac{\beta_{LogCost}}{cost})} \tag{5.3}$$

Equation 5.3 has been operationalised by multiplying the cost contribution

$\beta_{Cost} + \frac{\beta_{LogCost}}{cost}$ by the reciprocal of the real income growth between the base and transfer contexts, i.e. by $1/G$.

This approach makes the assumption that the marginal utility of time does not changes over time, i.e. is perfectly temporally transferable, so that changes in VOT occur solely as a result of changes in the marginal utility of cost. This assumption is discussed further in Section 5.4 in the light of the findings from empirical tests with the Toronto and Sydney datasets of the temporal stability of the travel time parameters.

5.1.2 Tests with Toronto data

The tests for the Toronto data were undertaken for the 1986, 1996 and 2006 datasets, in each case making transfers to the other two possible years of data. The 2001 data was excluded from these analyses because in the 'car avail' specification the linear cost parameter was insignificant[1]. Table 5.1 summarises the *improvement* in fit in the transfer context that results from reducing the cost parameters to take account of growth in income (measured by GDP/capita).

Table 5.1: Toronto income adjustment tests (detailed specification)

Base year	Transfer year		
	1986	1996	2006
1986	n/a	152.2	780.3
1996	123.7	n/a	-607.2
2006	419.9	-314.4	n/a

For four of the six tests, an improvement in fit in the transfer context is observed when the cost contribution is reduced by the growth in GDP/capita. For transfers

[1]Given that the 2001 data could not be used, the 'detailed' specification, the most detailed model specification, was used for these tests. The detailed specification cannot be estimated from the 2001 data because the age terms cannot be specified from the 2001 estimation file.

from 1996 to 2006, and from 2006 to 1996, adjusting the cost contribution by real growth in GDP/capita gave a worse fit than making no adjustment at all.

5.1.3 Tests with Sydney data

A key advantage of the Sydney data over the Toronto data is that incomes were recorded. By calculating the mean incomes in the base and transfer samples, Equation 5.3 could be operationalised using observed real income changes across the study area rather than by approximating the real income change using a GDP per capita measure.

In the best Sydney commute model specification (the 'detailed & income' specification) cost sensitivity is segmented by income. Specifically, there are three separate linear cost terms for different incomes bands, but a single log-cost parameter estimated across all income bands. The complication with applying Equation 5.3 in this model is that some of the growth in VOT G comes about due to a shift in the distribution of individuals into higher income bands between the base and transfer samples. If the G factor calculated from the observed change in mean real income is applied, then the effect of re-distribution will be to give an overall VOT adjustment greater than G.

To deal with this issue, a two-step procedure was employed. First, the cross-sectional income elasticity was calculated from the model parameters and the disaggregate incomes in the estimation sample using Equation 5.4.

$$E_{inc} = \frac{(\frac{\beta_H - \beta_L}{\beta_L})}{(\frac{inc_H - inc_L}{inc_L})} \tag{5.4}$$

where: β_L is linear cost parameter in the lowest income band

β_H is linear cost parameter in the highest income band
inc_L is the mean income in the lowest income band in the estimation sample
inc_H is the mean income in the highest income band in the estimation sample

The β_L and β_H parameters are defined in Table 4.10.

From the income elasticity it is possible to calculate income growth due to redistribution alone:

$$G_R = -E_{inc} * G \tag{5.5}$$

The remainder of the income growth can be viewed as a uniform increase G_U which is applied to across all income bands:

$$G_U = G - G_R \tag{5.6}$$

In the commute model, the linear cost parameters vary with income band. From Equation 5.2 it can be seen that the contribution of the linear cost term to the VOT calculation does not vary with the cost of the journey. However, in the home–other travel model the log-cost parameters vary with income band. It can be seen from Equation 5.2 that in a log-cost formulation, the contribution from the log-cost term increases with the cost of the journey, and higher income travellers tend to make longer and more expensive journeys. Thus to the extent that journey cost is correlated with income, the log-cost formulation itself accounts for an income effect, and so higher VOTs for higher travellers come about due to a combination of the log-cost parameters and more expensive journeys.

Table 5.2 summarises the values for the income growth components in the commute and home–other travel models calculated using Equations 5.4, 5.5 and 5.6. Following the discussion above, for home–other travel the elasticity values presented are for journeys of constant cost.

Table 5.2: Components of income growth in Sydney models

Purpose	Transfer	E_{inc}	G_R	G_U	G
commute	1991 to 2006	-0.38	1.120	1.198	1.318
	2006 to 1991	-0.32	1.102	1.216	1.318
home–other travel	1991 to 2006	-0.013	1.004	1.302	1.306
	2006 to 1991	0 (fixed)	0.000	1.306	1.306

For commute, cross-sectional elasticities E_{inc} of -0.38 and -0.32 were calculated. It can be seen from Table 5.2 that re-distribution therefore accounts for around one-third of the total income increase G.

For home–other travel, for transfers from 1991 to 2006 a much lower elasticity E_{inc} of just -0.013 was calculated. As per the discussion above, the much lower income elasticity follows from the fact that higher income travellers make more expensive journeys, and in a log-cost formulation this results in higher implied VOTs. For example, in the 1991 dataset the mean journey costs are \$0.95 in the lowest income band but \$1.56 in the highest income band.

For the 2006 dataset, the model results with the income segmented specification were implausible, as cost sensitivity was slightly higher in the top income band than the two lower income bands. Therefore for the transferability tests the 2006 parameters from the detailed specification (without income segmentation) were used, which means that E_{inc} is zero (from Equation 5.4) and all income growth is applied through the G_U adjustment[2].

[2]Constraining the income segmented log-cost parameters in the 'detailed & income' specification to be the same for each income band give a model equivalent to the 'detailed' specification.

Tables 5.3 and 5.4 summarise the results from the VOT adjustment tests for commute and home–other travel with the tables showing the *improvement* in model fit that results from applying the VOT adjustment.

Table 5.3: Sydney VOT adjustment tests, commute

Base year	obs	Model specification			
		sparse	car avail	detailed	detailed & income
1991 transfer to 2006	5,173	69.2	49.8	56.8	79.2
2006 transfer to 1991	5,111	55.9	48.3	31.4	45.3

Table 5.4: Sydney VOT adjustment tests, home–other travel

Base year	obs	Model specification			
		sparse	car avail	detailed	detailed & income
1991 transfer to 2006	10,464	84.2	24.1	11.5	13.1
2006 transfer to 1991	10,644	-339.7	-414.4	-433.7	-433.7

For both transfers of the commute models, and for the transfer of the 1991 home–other travel model to 2006, modest increases in fit to the data are observed across all four model specifications when the cost parameters are adjusted by the real income growth. However, for the transfer of the 2006 home–other travel model to 1991 the fit is substantially worse than when no adjustment is applied for all four model specifications[3].

5.1.4 Discussion

Overall, the tests on the Toronto and Sydney datasets presented in Tables 5.1, 5.3 and 5.4 demonstrate that adjusting the cost parameters by the real growth

[3]Given how poorly the 2006 models transfer to 1991 the setups were double-checked for errors but no issues were identified.

in income (i.e. using a longitudinal income elasticity of 1) gives an improved fit to the data relative to making no adjustment. For the Sydney commute models, cross-sectional income elasticities in the range -0.32 to -0.38 are observed. These values are in line with other evidence summarised in Daly and Fox (2012), who reported cross-sectional elasticities of around -0.3.

The approach developed for models that incorporate income segmentation that decomposes total income growth into redistribution between bands, and a further uniform increase applied across all bands, appears to work well. An important consideration that the analysis highlights for models that work with log-cost terms segmented by income band is that the cross-sectional elasticity may be considerably lower than -0.3; this results from the fact that higher income travellers tend to make more expensive journeys and these are subject to higher implied VOTs in a log-cost formulation.

5.2 Scale adjustment

In order to compare individual parameters between models estimated separately from each available year of the data, it was necessary to take account of scale differences between the models estimated for different years. To do this, models were estimated by pooling the data and estimating the parameters across all years of data. In these models, scale parameters were estimated relative to a base dataset to identify differences in scale between the different years of data.

5.2.1 Toronto data

For the Toronto data, pooled models for the three model specifications defined in Table 4.2 were jointly estimated from the 1986, 1996, 2001 and 2006 TTS datasets[4]. The 1986 scale was fixed to one, so all other datasets are scaled relative to the base 1986 data. The resulting scale parameter estimates are given in Table 5.5 (the t-ratios presented are calculated with respect to a value of 1).

Table 5.5: Toronto scale parameters

Year	Model specification					
	Sparse		Car avail		Detailed	
	scale	t-ratio	scale	t-ratio	scale	t-ratio
1986	1.000	n/a	1.000	n/a	1.000	n/a
1996	0.843	38.0	0.866	32.0	0.861	33.2
2001	0.963	8.0	0.920	18.3	n/a	n/a
2006	0.913	19.8	0.939	13.7	0.939	13.5

The results imply that the level of unexplained error is higher in the 1996, 2001 and 2006 databases, despite the fact that the level of detail in the zoning system has increased over time. The scale parameters presented in Table 5.5 were used to re-scale the parameters from the separately estimated models for 1996, 2001 and 2006 before individual parameters were compared. The model parameter values *after rescaling* are presented in Table 4.4 and in Appendix B.

A possible explanation for the pattern of increasing error with time is increased labour market specialisation, and the associated decentralisation of employment away from central areas, which may make it more difficult to explain commuter destination choice. Statistics Canada (2003) have found that the majority of employment growth over recent decades has taken place in suburban municipalities of urban areas, with a 61% increase in employment in these areas between 1981 and 2001 compared to a 7% increase in central municipalities over the same period. This is consistent with analysis of the model estimation results, which showed that the percentage of commute tours travelling to zones in the Central Business District declined from 8.8% in 1986 to 5.9% in 2006.

[4]The pooled model for the detailed specification omits the 2001 data because the 2001 data does not contain the age information required to estimate that specification.

5.2.2 Sydney data

For the Sydney data, pooled models were run where scale parameters for the 1991 data were estimated relative to the 2006 data. The scale parameters that were estimated are given in Table 5.6 for commute and 5.7 for home–other travel (the t-ratios presented are calculated with respect to a value of 1).

Table 5.6: Sydney scale parameters, commute

Year	Model specification							
	Sparse		Car avail		Detailed		Detailed & income	
	scale	t-ratio	scale	t-ratio	scale	t-ratio	scale	t-ratio
1991	0.947	4.4	0.968	2.5	0.968	2.5	0.952	3.8
2006	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a

Table 5.7: Sydney scale parameters, home–other travel

Year	Model specification							
	Sparse		Car avail		Detailed		Detailed & income	
	scale	t-ratio	scale	t-ratio	scale	t-ratio	scale	t-ratio
1991	0.823	29.9	0.827	26.8	0.811	31.9	0.811	31.7
2006	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a

The scale parameters indicate a higher level of error in the 1991 data relative to the 2006 data. A factor that will contribute to this result is the substantial increase in the number of zones between 1991 and 2006, from 845 to 2,277. For public transport, walk and cycle in modes in particular the use of a more detailed zone system will give more realistic level of service and this will contribute to the lower level of error in the 2006 data.

5.3 Significance of parameter differences

To test the transferability of individual parameters, Equation 2.25 was applied to test whether pairs of parameters were significantly different from one another. The following subsections present the results of these tests for the Toronto and Sydney data.

5.3.1 Toronto data

This analysis has been undertaken taking both the 1986 parameters as the base, and the 2006 parameters as the base. The results have been summarised separately for the cost terms, the level of service terms, the mode and destination constants, and the socio-economic constants (as per the classification detailed in Table 4.2.3) to investigate whether different types of model parameter are more transferable. The results are presented in Table 5.8 and Table 5.9, which summarise the number of parameters that are not significantly different from the 1986 and 2006 base values at a 95% confidence level.

Table 5.8: Parameters that are not significantly different, 1986 base

Parameter group	Sparse specification			Car avail specification			Detailed specification		
	1996	2001	2006	1996	2001	2006	1996	2001	2006
cost terms	0/2	0/2	0/2	0/2	0/2	0/2	0/2	n/a	0/2
level of service terms	2/6	0/6	4/6	2/6	2/6	3/6	2/6	n/a	4/6
mode and dest. constants	1/5	1/5	1/5	1/5	1/5	1/5	2/5	n/a	2/5
socio-economic terms	n/a	n/a	n/a	0/3	0/3	2/3	2/8	n/a	4/8
Total	3/13	1/13	5/13	3/16	3/16	6/16	6/21	n/a	10/21

Overall, the null hypothesis that the base and transfer parameters are not significantly different is rejected for the majority of parameters. It might be expected that the hypothesis that parameters are not significantly different would be more likely to be accepted for short transfers, however no clear pattern of variation with

Table 5.9: Parameters that are not significantly different, 2006 base

Parameter group	Sparse specification			Car avail specification			Detailed specification		
	2001	1996	1986	2001	1996	1986	2001	1996	1986
cost terms	0/2	0/2	0/2	0/2	0/2	0/2	0/2	n/a	0/2
level of service terms	1/6	1/6	4/6	2/6	2/6	3/6	2/6	n/a	4/6
mode and dest. constants	0/5	0/5	1/5	1/5	0/5	1/5	0/5	n/a	2/5
socio-economic terms	n/a	n/a	n/a	0/3	3/3	2/3	4/8	n/a	4/8
Total	1/13	1/13	5/13	3/16	5/16	6/16	6/21	n/a	10/21

length of transfer is apparent. Comparing across the three model specifications, then if comparisons are restricted to the three parameter groups present in all three model specifications, there is no clear pattern of increasing transferability with improved model specification.

No clear pattern emerges when comparing across the four parameter groups. The hypothesis of parameter equality is always rejected for the cost parameters, but there are only two cost parameters in each comparison and the clear majority of all comparisons reject the hypothesis of parameter equality.

5.3.2 Sydney data

For the Sydney models, the analysis of significance of parameter differences has been calculated with the 1991 parameters as the base. Table 5.10 summarises the results from the analysis of the significance of differences in the commute parameters. The tests have been undertaken using a 95% confidence level, and the classification of each individual parameter into the four groups is detailed in Table 4.10.

Like the Toronto analysis presented in Table 5.8 and Table 5.9, the hypothesis of parameter equality is rejected for the majority of parameter comparisons in Ta-

Table 5.10: Parameters that are not significantly different, Sydney commute models

Parameter group	Model specification			
	Sparse	Car avail	Detailed	Detailed & income
cost terms	1/2	1/2	1/2	1/4
level of service terms	7/9	7/9	7/9	7/9
constants	3/10	0/10	1/10	0/10
socio-economic terms	n/a	2/3	4/8	4/8
Total	11/21	10/24	13/29	12/31

ble 5.10. However, unlike the Toronto analysis clear patterns emerge comparing across the parameters. The hypothesis of parameter equality is rejected for most of the constants, whereas in most cases the level of services terms are not significantly different. The cost and socio-economic terms lie somewhere between. Thus these results suggest that there are differences in transferability across different types of model parameters.

Table 5.11 presents analysis of parameter differences for the home–other travel model. The allocation of individual parameters into the four parameters groups is given in Table 4.12.

Table 5.11: Parameters that are not significantly different, Sydney home–other travel models

Parameter group	Model specification			
	Sparse	Car avail	Detailed	Detailed & income
cost terms	0/1	0/1	0/1	0/3
level of service terms	3/8	4/8	4/8	4/8
constants	7/10	1/10	1/10	1/10
socio-economic terms	n/a	0/2	3/9	3/9
Total	11/19	5/21	8/28	8/30

Overall, the results in Table 5.11 indicate that the home–other travel parameters are less transferable than the home-work parameters. However, the patterns of variation between parameter groups are similar, with the hypothesis of parameter equality rejected for most of the constants, and with the hypothesis of parameter equality more likely to be accepted for the level of service terms.

5.3.3 Discussion

A limitation of the significance of parameter differences is that the hypothesis that the parameters are equal is less likely to be rejected if the parameters are imprecisely estimated. For example, the level of service terms in the Toronto commute models are precisely estimated, with t-ratios ranging from 11 to 50, and this means that the hypothesis that the parameters are equal is rejected even when the parameters are relatively close in magnitude. In the following section, the relative changes in the parameter values are analysed using a measure that is independent of the significance of the parameter estimates.

While the results for the Sydney models are subject to the same limitation, they do suggest that the constants are the least transferable parameter group, and the level of service terms the most transferable. The analysis of the Sydney models also indicates that the commute parameters are more transferable than the home–other travel parameters. In Section 5.4, differences in the relative changes in the parameter values for the two purposes are compared.

5.4 Relative changes in parameter values

The REM measure defined in Equation 2.27 has been used to calculate the absolute change in individual parameter values relative to the base parameter values accounting for the overall difference in scale between the base and transfer models. These differences have been calculated separately for the cost terms, the level of service terms, the mode and destination constants, and the socio-economic terms. For each model analysed, average values have been calculated for each of these parameter groups.

5.4.1 Toronto data

Table 5.12 summarises the results obtained. It is possible that the 1986 parameters are more transferable, or less transferable, than the parameters for other years of data. To avoid producing results that are specific to a particular base year, the analysis has been repeated taking the 2006 parameters as the base. These results are presented in Table 5.13.

Table 5.12: REM measures by model year and specification, 1986 base

Parameter group	Model specification								
	Sparse			Car avail			Detailed		
	1996	2001	2006	1996	2001	2006	1996	2001	2006
cost terms	0.47	1.42	0.36	0.52	1.61	0.38	0.50	n/a	0.37
level of service terms	0.10	0.20	0.10	0.09	0.16	0.12	0.09	n/a	0.11
constants	0.51	2.25	1.67	0.75	2.44	2.56	0.65	n/a	2.76
socio-economic terms	n/a	n/a	n/a	0.17	0.29	0.17	0.30	n/a	0.42

Comparing between different groups of utility terms, the cost, LOS terms and socio-economic terms show smaller changes in parameter magnitude over time compared to the mode and destination constants. This result is expected, as the constants capture the mean contributions of effects not captured in the other parameters, and the contributions of these uncaptured effects would be expected to change over time.

Table 5.13: REM measures by model year and specification, 2006 base

Parameter group	Model specification								
	Sparse			Car avail			Detailed		
	1996	2001	2006	1996	2001	2006	1996	2001	2006
cost terms	1.03	0.88	0.36	1.08	0.88	0.33	n/a	0.88	0.34
level of service terms	0.19	0.11	0.09	0.18	0.10	0.10	n/a	0.11	0.10
constants	2.82	5.93	3.91	0.67	1.93	1.49	n/a	1.70	1.32
socio-economic terms	n/a	n/a	n/a	0.11	0.04	0.14	n/a	0.16	0.31

The REM measures for the cost terms do not exhibit any consistent pattern of evolution over time, with the largest differences between parameters observed by comparing the 1986 and 2001 parameter values. They do not reduce with improving model specification either, with the largest differences observed for the car avail specification.

The LOS parameters show the smallest REM measures for all but two of the transfer tests, i.e. in general the LOS parameters are more transferable than the other parameter groups. Comparing across model specifications, with the exception of the 20 year transfers, the REM measures reduce between the sparse and car avail specifications when the car availability parameters are added. Thus improving the model specification by adding additional socio-economic terms improves the transferability of the LOS parameters over transfer periods up to 15 years in duration. However, there is no further improvement in the transferability of the LOS parameters when the age and gender mode terms are added in the detailed specification. Examining the changes in parameter values over time reveals no clear patterns.

The socio-economic parameters show relatively small changes over time, particularly when the changes are calculated relative to the 2006 model, which indicates that the socio-economic effects are transferable over time. Interestingly, the mean

REM measures are larger for the detailed specification models than for the car avail specification models. This is because the car availability parameters are more transferable than the age and gender parameters introduced in the detailed specification.

As discussed in Section 5.1, when applying the adjustments to account for real growth in VOT with income it has assumed that the growth in VOT can be applied by making adjustments to the cost parameter alone, rather than adjusting both the cost and time parameters (the implied VOT is calculated as function of the two). To investigate the validity of this assumption, changes in the values of cost and time parameters from the detailed specifications were analysed, calculating changes relative to the 1986 base parameters. The analysis is presented in Table 5.14, in which the model results presented in Table 4.4 have been used to calculate the change in the parameter values relative to the 1986 base values.

Table 5.14: Changes in Toronto cost and in-vehicle time parameters, 1986 base

Parameter	1986	1996		2006	
Log(cost)	-0.358	-0.575	61%	-0.335	-6%
Cost	-0.0011	-0.0006	-42%	-0.0016	48%
Car time	-0.042	-0.038	-8%	-0.044	5%
Transit IVT	-0.028	-0.029	2%	-0.025	-10%

The in-vehicle time parameters are relatively stable over time, with the 1996 and 2006 values within ± 10% of the 1986 values. The cost parameters are considerably less stable, with differences of up to 60% observed despite accounting for real income growth.

5.4.2 Sydney data

Table 5.15 presents the REM measures for the Sydney commute models, with the REM measures calculated for changes relative to the 1991 parameters.

Table 5.15: REM values for parameter changes, Sydney commute models

Parameter group	Model specification			
	Sparse	Car avail	Detailed	Detailed & income
cost terms	0.215	0.223	0.240	0.447
level of service terms	0.143	0.152	0.145	0.145
constants	0.857	0.915	0.902	1.097
socio-economic terms	n/a	0.190	0.383	0.445

The commute results are consistent with those observed in the Toronto analysis, with the level of service of service terms showing the highest level of transferability, and with noticeably lower levels of transferability for the constants relative to the other three groups. A result common to both the Toronto and Sydney commute models is that lower REM measures are observed for the car availability terms than the other socio-economic terms introduced in the detailed specification.

Table 5.16 presents the REM measures for the Sydney home–other travel models, with the REM measures again calculated for changes relative to the 1991 parameters.

Table 5.16: REM values for parameter changes, Sydney home–other travel models

Parameter group	Model specification			
	Sparse	Car avail	Detailed	Detailed & income
cost terms	0.480	0.335	0.377	0.401
level of service terms	0.474	0.427	0.419	0.346
constants	0.199	3.483	3.533	1.448
socio-economic terms	n/a	0.417	0.485	0.503

In most cases the REM values for the home–other travel parameters are higher than those for the commute models, indicating the models to be less transferable. Consistent with commute, the constants show the highest levels of error, but unlike the commute models the level of service terms are not more transferable than the cost and socio-economic terms. A possible explanation for this result is that the home–other level of service terms are more impacted by the changes in the modelled highway distances and travel times that come about as a result of changes in the model zoning between 1991 and 2006 (discussed in Section 3.3.2) because home–other travel tours are shorter on average than commute tours.

Analysis has also been undertaken to investigate the impact on parameter transferability of estimating models for three sub-purposes that cover home–other travel:

- serve passenger
- personal business
- leisure

Table 5.17 presents analysis comparing the REM values for these three sub-purposes to those obtained from an overall home–other travel model. The tests were undertaking using the detailed specification (i.e. without income segmentation) as the income terms in the detailed & income specification were not always significant for the sub-purposes.

Table 5.17: Sydney home–other travel sub-purpose tests, REM measures

	All purposes	Serve passenger	Personal business	Leisure	Mean
Cost	0.226	0.202	0.259	0.170	0.211
LOS	1.113	0.589	1.413	0.399	0.800
Constants	2.059	0.943	0.551	1.216	0.903
Socio-econ.	0.495	0.724	0.307	0.390	0.474
Mean	0.973	0.614	0.633	0.544	0.597

It can be seen that the mean REM values is lower for all three of the sub-purposes than for the all purposes model. In particular, the REM values for the constants are considerably lower in the sub-purpose models reflecting differences in mode share and destination choice, and the level of service parameters also have somewhat lower REM values. Overall the results suggest segmenting other travel does give rise to more transferable model parameters.

Table 5.18 and Table 5.19 show the changes in the cost and in-vehicle time parameters between the 1991 and 2006 models for the detailed specification, i.e. the best specification prior to the introduction of income segmented cost parameters (the full set of parameter results for these two model are presented in Tables C.3 and C.5 of Appendix C).

Table 5.18: Changes in Sydney commute cost and in-vehicle time parameters

Parameter	1991	2006	
Log(cost)	-0.445	-0.327	-26%
Cost	-0.00035	-0.00027	-22%
Car time	-0.027	-0.031	15%
Rail IVT	-0.012	-0.013	11%
Bus IVT	-0.022	-0.021	-6%

Table 5.19: Changes in Sydney home–other travel work cost and in-vehicle time parameters

Parameter	1991	2006	
Log(cost)	-1.124	-0.700	-38%
Car time	-0.053	-0.066	25%
Rail IVT	-0.022	-0.016	-25%
Bus IVT	-0.023	-0.029	23%

For both models, the in-vehicle time parameters are more stable over time than the cost parameters, through the changes in the in-vehicle time parameters are greater than those observed in the Toronto models in Table 5.14, particularly for home–other travel. A relevant factor when considering changes in the Sydney parameters is the significantly more detailed zone system used for the 2006 models. As discussed in Section 3.3.2, these changes would be expected to have more impact on shorter tours which is consistent with the larger changes in the home–other travel in-vehicle time parameters.

5.4.3 Discussion

The finding that the LOS parameters are more transferable than other parameter types is consistent with the analysis of parameter changes from other mode choice and mode-destination choice models reported in the literature. The magnitudes of the mean parameter differences presented in Tables 5.12 and 5.13 are also broadly consistent with the values reported in other studies summarised in Table A.1 of Appendix A. Habib et al. (2012) estimated mode choice models for Toronto (using the same TTS data that have been used for this analysis) for 1996, 2001 and 2006, and also found that the LOS parameters were more transferable than the cost parameters.

The REM measures for the mode and destination constants show much larger differences in parameter values between years, and indeed some constants have changed sign between years. Thus the stability of these parameters over time is poor. This result is consistent with the analysis of Habib and Weiss (2014) who estimated mode choice models incorporating modal captivity using the TTS data for 1996, 2001 and 2006, and found that the constants showed larger changes between year than the other parameters. The finding that the constants show greater changes between years than other model parameters suggests that improving model specification, which will reduce the role of the constants relative to other model terms, would be expected to improve model transferability. This hypothesis is confirmed by analysis presented in Chapter 6.

In summary, the level of service and socio-economic terms are more transferable than the other terms. The cost terms are considerably less transferable than the level of service terms, and the least transferable parameters are the mode and destination constants, which implies that reducing the role of the constants by improving model specification would be expected to improve model transferability.

Many transport policies are formulated principally in terms of changes in cost and/or travel time, and so the degree of stability in the cost and in-vehicle time parameters is a particularly relevant consideration of model transferability. For the Toronto commute models, the in-vehicle time parameters show a high level of stability, and the Sydney commute models also show a reasonable level of stability. For home–other travel a lower level of stability was observed, but this result seems to be influenced by changes in the modelled highway level of service rather than real changes in behaviour. For all comparisons, the cost parameters are less transferable than the in-vehicle time parameters, despite accounting for real income growth. These results suggest the models are better placed to assess the impact of policies whose main impact is changes in travel time than to assess policies whose main impact is changes in travel costs.

The stability in the in-vehicle time parameters in the Toronto models, and to a lesser extent the Sydney models, suggests that the assumption made in Section 5.1.1 that VOT growth can be applied through adjustments to the cost parameters while assuming sensitivity to travel time is constant over time is reasonable. This result is consistent with the findings of Börjesson (2014), who observed a high degree of stability in the time parameters in models estimated from Swedish stated preference value of time data collected in 1994 and 2007.

5.5 Values of time

Values of time (VOTs) are key to transport modelling as they provide a measure of how individuals trade off travel cost and travel time. In models with separate cost and time parameters such as those used for this transferability analysis, validation of the implied values of time is a key step as it ensures that the cost-time trade offs in the models are consistent with other evidence, such as the UK Department for Transport's WebTAG guidance. Therefore analysis has been undertaken to examine the transferability of the VOT relationships over time.

As detailed in Section 5.1.1 the VOT for the utility functions presented in Chapter 4 can be calculated from the following relationship:

$$VOT = \frac{\partial U / \partial time}{\partial U / \partial cost} = \frac{\beta_{Time}}{\beta_{Cost} + \frac{\beta_{LogCost}}{cost}} \tag{5.7}$$

where: β_{Time} is the travel time parameter
β_{Cost} is the linear cost parameter
$\beta_{LogCost}$ is the log cost parameter
$cost$ is the modelled cost

It can be seen from Equation 5.7 that the VOT for a given journey depends on both the model parameters and the cost of the journey. For each year of data, Equation 5.7 can be applied to each individual tour record and an average VOT calculated. However, even if the model parameters were perfectly transferable, if the mean journey cost changes over time then the mean VOTs will also change. As shown by Tables 3.6 and 3.12, mean car costs have increased significantly over time and this results in higher implied VOTs.

Therefore the approach that has been followed is to plot the variation in VOT withe journey cost. This allows the VOT relationships to be compared over a range of journey costs, and further allows the impact of changes in the relative contribution of the linear and log cost parameters to be visualised. It should be noted that these comparisons are made *after* applying the adjustment to take account of real terms income growth set out in Section 5.1.1.

5.5.1 Toronto data

VOTs have been calculated using the parameters from the detailed model specification. The analysis has been undertaken using the 1986, 1996 and 2006 model parameters[5] for car driver and for PT.

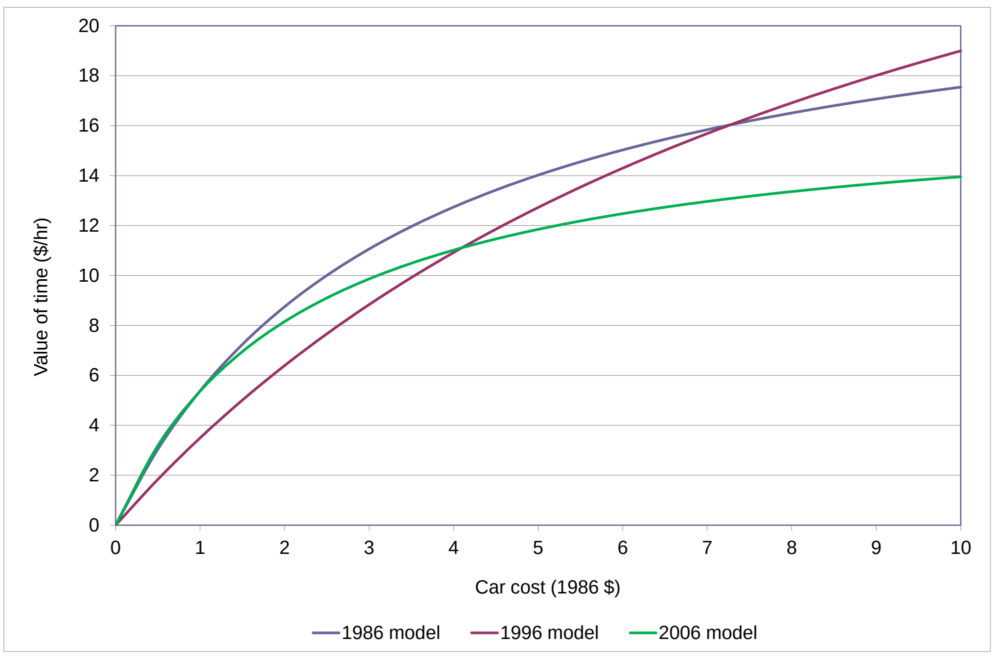

Figure 5.1: Variation in Toronto car values of time with journey cost

The mean car costs in 1986 prices are $2.00 for the 1986 data, $2.30 for the and $3.60 for the 2006 data. Over this cost range it can be seen that the 1986 and

[5] In the 2001 model results, the log-cost term insignificant and wrong-signed (positive) and so the 2001 results were omitted from this analysis.

2006 VOT relationships match closely, i.e. the VOTs are highly transferable, whereas somewhat lower VOTs are observed in the 1996 model due to the more linear VOT relationship for 1996.

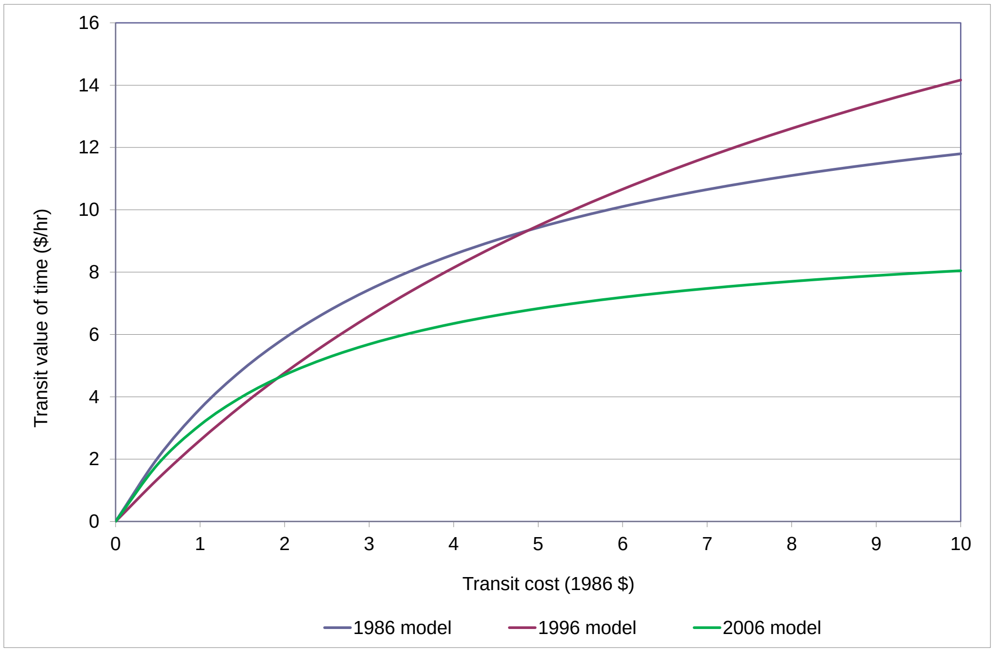

Figure 5.2: Variation in Toronto PT values of time with journey cost

The mean PT costs in 1986 prices are $1.70 for the 1986 data, $3.20 for the and $2.60 for the 2006 data. Over this cost range 1996 and 2006 VOT relationships correspond closely, whereas the VOTs in the 1986 model are somewhat higher.

5.5.2 Sydney data

For commute, car VOTs have been calculated for the detailed & income model specification. In this model specification, VOTs vary with income band as well as journey cost and so the VOT relationships are plotted separately by the four income bands B1 to B4 defined in Section 4.3.3[6]. The VOTs are plotted in Figure 5.3 in which the solid lines show the VOT relationships for 1991, the dashed lines show the VOT relationships for 2006, and the same colour is used for the 1991 and 2006 for a given income band. Note that the y-axis chosen truncates the VOTs for the higher income bands at higher costs so that the relationships for lower income bands can be more clearly distinguished.

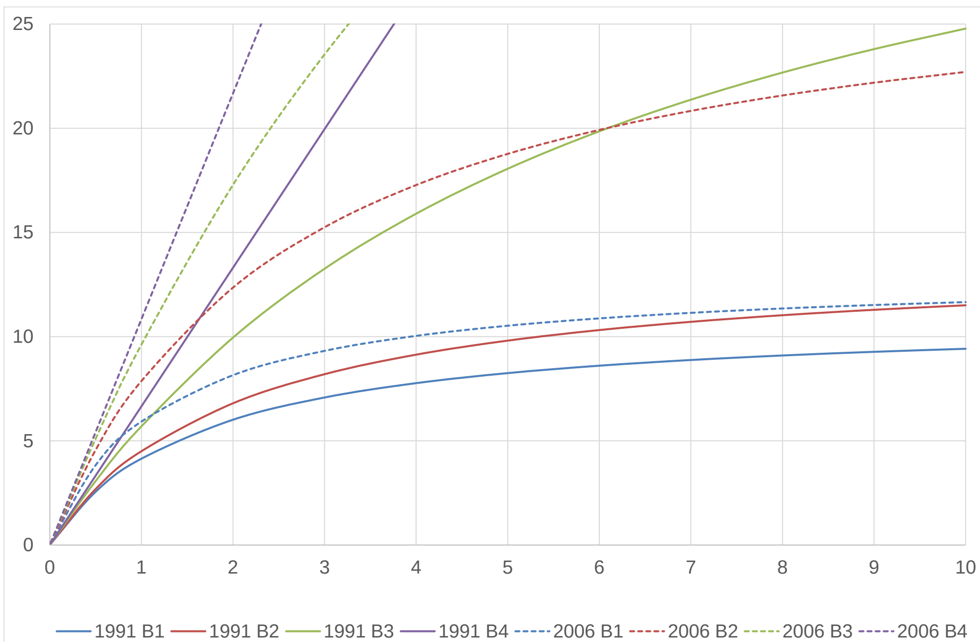

Figure 5.3: Variation in Sydney commute car values of time with journey cost and income band

For all income bands, the 2006 VOTs are higher for a given tour cost than the 1991 costs, particularly for the second income band where the 2006 VOTs are around twice the 1991 VOTs. Analysis of the changes in the time and cost parameters

[6]Note that in the top band ($36.4k+), there is no linear cost term and so cost sensitivity is determined by the log-cost parameter alone.

which enter into the VOT calculation showed that the VOT increases results from both a reduction in the magnitude of the cost parameters and an increase in the magnitude of the car time parameter. It can be seen from Equation 5.7 shows that both of these changes work to increase the VOTs.

For home–other, for 2006 the income terms in the detailed & income specification were not significant, and therefore the VOTs have been compared for the detailed specification without income specification. Figure 5.4 illustrates how the car VOTs vary with journey cost.

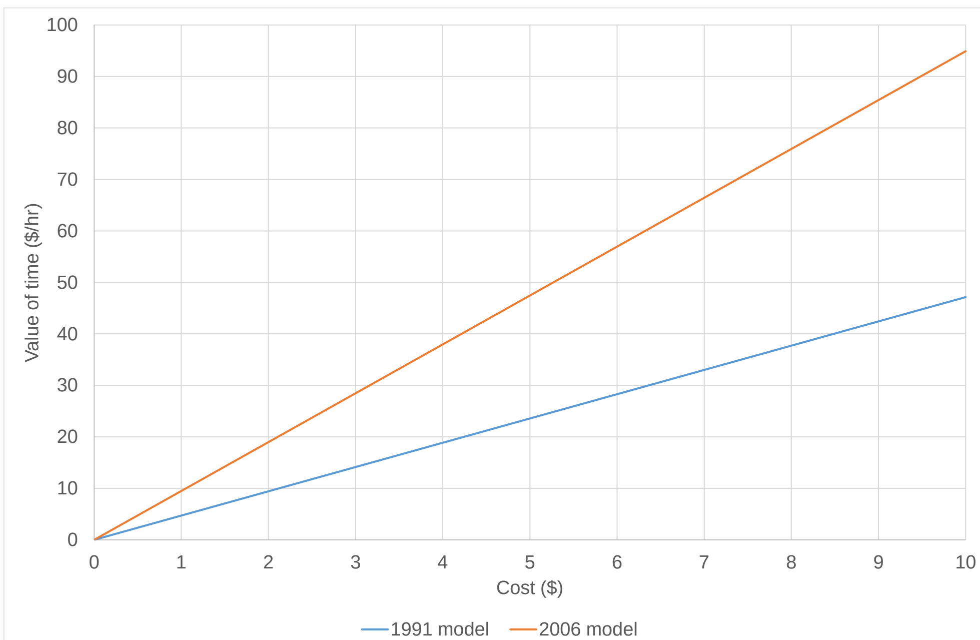

Figure 5.4: Variation in Sydney commute car values of time with journey cost and income band

The 2006 VOTs are significantly higher than the 1991 values, consistent with the commute results. Again this result follows from changes to the relative magnitude of the cost and time parameters, and as discussed in Section 5.4.2 these changes are believed to be impacted by the change in the zone system between 1991 and 2006 and the resulting changes to mean distances and travel times. Thus the changes to the Sydney VOT relationships are believed to be strongly influenced by the changes in the level of service.

5.5.3 Discussion

The Toronto car and PT VOT relationships show a reasonably good level of temporal transferability. However, for Sydney significant increases in implied VOT are observed between 1991 and 2006 due to changes in the relative strength of the travel time and cost terms, and these changes are believed to be influenced by the changes in level of service that follow from the changes to the zoning system.

The Sydney result illustrates the limitation of using models of the this type with separate cost and in-vehicle time parameters to calculate VOTs, namely that if the cost terms reduce in explanatory power then given car cost and car time are highly correlated and the car modes tend to dominate the overall mode share, then the car time term term will tend to increase in magnitude and these changes result in a larger percentage change in VOT than the percentage change in the cost and time parameters. In summary, the implied car VOTs are strongly influenced by the relative strength of the cost and car time parameters.

5.6 Structural parameters

5.6.1 Toronto data

The structural tests to investigate the relative sensitivity of the mode and destination choices were undertaken using the base 1986 data. These tests demonstrated that the best fit to the data was obtained using a structure with destinations above modes, which implies mode choice is more sensitive to changes in utility than destination choice. The destinations above modes structure remained valid for all model specifications, and furthermore was valid when the model specifications were estimated using the 1996, 2001 and 2006 data. Table 5.20 summarises the structural parameters that have been estimated. The t-ratios presented in brackets define the significance of the structural parameters relative to a value of one.

Table 5.20: Toronto commute models, relative sensitivity of destination and mode choice

Specification	1986	1996	2001	2006
Sparse	0.862 (9.6)	0.858 (9.9)	0.907 (5.5)	0.865 (8.1)
Car avail	0.814 (13.4)	0.773 (17.0)	0.761 (16.8)	0.768 (17.5)
Detailed	0.815 (12.8)	0.782 (15.6)	n/a	0.785 (13.6)

5.6.2 Sydney data

In the Sydney models, the best fit to the 1991 data was obtained with a modes above destinations structure which is the other way up to the best Toronto structure. Table 5.21 summarises the structural parameters that have been estimated for the commute models.

For the 2006 data, the freely estimated values of the structural parameters were

Table 5.21: Sydney commute models, relative sensitivity of destination and mode choice

Specification	1991	2006
Sparse	0.737 (6.6)	1.0 (*)
Car avail	0.726 (6.7)	1.0 (*)
Detailed	0.729 (6.6)	1.0 (*)
Detailed & income	0.695 (7.9)	1.0 (*)

greater than one and therefore the parameter was constrained to one. It would have been possible to estimate the opposite structure (destinations above modes), however the transferability tests were for transferring the 1991 specification to 2006 and so the 1991 specification was retained.

Table 5.22: Sydney home–other travel models, relative sensitivity of destination and mode choice

Specification	1991	2006
Sparse	0.500 (15.3)	0.650 (10.0)
Car avail	0.450 (16.9)	0.582 (11.8)
Detailed	0.416 (17.2)	0.581 (11.8)
Detailed & income	0.399 (18.3)	0.594 (11.2)

The 2006 home–other travel structural parameters do not reject the destinations below modes structure, but they do show a pattern of increase between 1991 and 2006, consistent with the commute results. This suggests that the *relative* errors in destination and mode choice have reduced between 1991 and 2006 it could be that the mode choice error has reduced which may relate to the changes in level of service associated with the change in zoning system discussed in Section 3.3.2. Note that this result does not necessarily mean that the destination choice error has increased, it could equally be explained by a reduction in the mode choice error.

5.6.3 Discussion

The Toronto commute structural parameters demonstrate a good level of transferability over time, with the values for 1996, 2001 and 2006 all within $\pm$ 7% of the 1986 values, and for all tests the structural parameters are significantly lower than one. Thus these results suggest that the Toronto nesting structures are transferable over time.

For the Sydney models, the structural parameters for the destinations below modes structure have moved closer to 1 between 1991 and 2006, indicating that the errors in destination choice have increased *relative* to the errors in mode choice. This result may be related to the changes in level of service that follow from the substantial changes to the model zone system between 1991 and 2006.

It is noteworthy that while the Toronto structural parameters are transferable over time, comparison of the Toronto and Sydney commute values demonstrates that they are not spatially transferable.

Chapter 6

Model transferability

This chapter presents analysis of model transferability undertaken using both the Toronto and Sydney datasets.

Sections 6.1 and 6.2 present results from statistical tests of model transferability, including analysis of how model transferability varies with model specification and length of transfer period, and for the Sydney data analysis of how the transferability of commute and home–other travel models compare.

Section 6.3 investigates the ability of transferred models to predict observed changes mode share and observed tour length by mode.

The Chapter concludes in Section 6.4 with analysis of how the model elasticities vary between different base years, and how base and transfer model elasticities compare for a given year.

Earlier results from the analyses presented in Sections 6.2 and 6.3 were presented in Fox et al. (2014).

6.1 Transferability test statistic

A strict pass/fail test of model transferability is the Transferability Test Statistic (TTS), defined earlier in Section 2.3.1 but specified again here as the measure is referred to throughout this section:

$$TTS_t(\beta_b) = -2(LL_t(\beta_b) - LL_t(\beta_t)) \tag{6.1}$$

where: $LL_t(\beta_b)$ is the fit (log-likelihood) of the base model to the transfer data
$LL_t(\beta_t)$ is the fit for the model re-estimated on the transfer data

This section presents the results of TTS tests using the Toronto and Sydney datasets.

6.1.1 Toronto data

The results from the TTS tests are presented in Table 6.1 to Table 6.3, in which the title gives the number of degrees of freedom (d.o.f.) and the critical value for the TTS statistic at a 99.5% confidence level, the rows define the base year, the columns define the transfer year and the cell values give the values of the TTS statistic.

Table 6.1: TTS tests, sparse specification: 14 d.o.f., $\chi^2_{99.5\%} = 31.3$

Base	Transfer year			
year	1986	1996	2001	2006
1986	n/a	3652.3	4241.3	2460.1
1996	2795.6	n/a	4923.7	4936.8
2001	4330.6	4822.5	n/a	3225.8
2006	3309.9	2824.2	4019.2	n/a

It can be seen that the hypothesis of parameter equality is strongly rejected in

Table 6.2: TTS tests, car avail specification: 17 d.o.f., $\chi^2_{99.5\%} = 35.7$

Base year	Transfer year 1986	1996	2001	2006
1986	n/a	3,292.4	4,308.2	2,282.1
1996	2,373.9	n/a	4,236.0	5,096.7
2001	4,006.8	4,433.7	n/a	3,228.1
2006	3,095.0	3,083.2	4,113.7	n/a

Table 6.3: TTS tests, detailed specification: 22 d.o.f., $\chi^2_{99.5\%} = 42.8$

Base year	Transfer year 1986	1996	2001	2006
1986	n/a	3,372.9	n/a	2,517.1
1996	2,739.2	n/a	n/a	5,222.2
2001	n/a	n/a	n/a	n/a
2006	3,579.6	3,180.8	n/a	n/a

all comparisons.

6.1.2 Sydney data

Table 6.4 and Table 6.5 summarises the TI values calculated for the Sydney commute and home–other travel models for the two possible model transfers.

Table 6.4: TTS tests, Sydney commute models

	Model specification Sparse	Car avail	Detailed	Detailed & income
degrees of freedom	21	24	29	31
$\chi^2_{99.5\%}$	41.4	45.6	52.3	55.0
1991 to 2006	240.3	260.8	386.6	436.1
2006 to 1991	326.0	352.3	493.5	500.6

Consistent with the Toronto analysis, the hypothesis of parameter equality is strongly rejected for all possible transfers.

Table 6.5: TTS tests, Sydney home–other travel models

	Model specification			
	Sparse	Car avail	Detailed	Detailed & income
degrees of freedom	21	23	30	32
$\chi^2_{99.5\%}$	41.4	44.2	53.7	56.3
1991 to 2006	1,502.8	1,246.8	1,362.4	1,425.2
2006 to 1991	2,706.1	2,649.7	2,797.8	2,823.5

6.1.3 Discussion

It can be seen that the hypothesis of parameter equality in the base and transfer contexts is strongly rejected for all possible transfers with both the Toronto and Sydney datasets.

It is emphasised that rejection of the hypothesis of parameter equality does not mean that the models are not useful for predicting behaviour in the transfer context. As was discussed in Section 2.3.3, other researchers have found the TTS to be an over-restrictive definition of transferability. In particular, the model constants would not be expected to be transferable between base and transfer contexts, and so achieving perfect transferability is unlikely, and the analysis presented in Section 5.4 has confirmed that the model constants are less transferable than the other parameters. Thus the assessments of model transferability have focussed on the Transferability Index which provides a *relative* measure of transferability instead of a strict pass/fail test (Section 6.2), measures of the ability of the transferred models to predict the observed mode and destination choices in the transfer context (Section 6.3), and analysis of the evolution of the model elasticities (Section 6.4).

6.2 Transferability index

The Transfer Index (TI) measures the predictive accuracy of the transferred model relative to a locally estimated model, with an upper bound of one. It was discussed in Section 2.3.1 but is defined again here:

$$TI_t(\beta_b) = \frac{LL_t(\beta_b) - LL_t(\beta_t^{ref})}{LL_t(\beta_t) - LL_t(\beta_t^{ref})} \tag{6.2}$$

where: β_t^{ref} is the reference model for the transfer data
$LL_t(\beta_t) \geq LL_t(\beta_b) \geq LL_t(\beta_t^{ref})$

A reference model is used in the calculation of TI. As discussed in Section 2.3.1, the reference model used for this analysis has constants and tour distance terms by mode so that the observed shares and tour lengths by mode are replicated by the reference model.

6.2.1 Toronto data

Four different years of TTS data are available for analysis, and models estimated from a given year can be transferred to the data for the three other years. Therefore a total of 12 different transfers can be made. Transfers have been undertaken for the spare, car avail and detailed model specifications A (except for transfers to/from the 2001 data, where only the sparse and car avail specifications can be estimated). Building on the analysis presented in Section 5.1.1, all model transfers have been undertaken by adjusting costs by the growth in GDP/capita relative to 1986[1].

Table 6.6 to Table 6.8 summarise the resulting TI values for the three model

[1]Noting that for all years of data, the cost parameters have been estimated in 1986 values.

specifications tested.

Table 6.6: Toronto commute TI values, sparse specification

Base year	Transfer year 1986	1996	2001	2006
1986	n/a	0.55	0.71	0.71
1996	0.66	n/a	0.67	0.41
2001	0.48	0.40	n/a	0.61
2006	0.60	0.65	0.73	n/a

Table 6.7: Toronto commute TI values, car avail specification

Base year	Transfer year 1986	1996	2001	2006
1986	n/a	0.71	0.78	0.81
1996	0.78	n/a	0.78	0.57
2001	0.63	0.61	n/a	0.73
2006	0.72	0.73	0.79	n/a

Table 6.8: Toronto commute TI values, detailed specification

Base year	Transfer year 1986	1996	2001	2006
1986	n/a	0.75	n/a	0.82
1996	0.79	n/a	n/a	0.63
2001	n/a	n/a	n/a	n/a
2006	0.73	0.76	n/a	n/a

Examining the TI values for the sparse specification first, the TI values might be expected decline with the length of the transfer period, but no clear pattern of variation with transfer period emerges. Coming on to the TI values for the car avail specification, the first observation is that the TI values are higher than those for the sparse specification for each of the the 12 transfers. Therefore improving the model specification with the addition of car availability terms has consistently improved the transferability of the models. The TI values for the detailed specification are in turn consistently higher than those for the car avail specification, and therefore the finding that transferability improves with model specification is again demonstrated for each possible transfer.

Table 6.8 demonstrates that for the detailed model specification, on average the transferred models explain, relative to the reference model, 75-80% of behaviour explained by the models re-estimated on the transfer data.

To summarise these results, Figure 6.1 presents the mean TI values by transfer period and model specification. Figure 6.1 clearly demonstrates that there is no trend for the Toronto TI values to decrease with increasing length of transfer period.

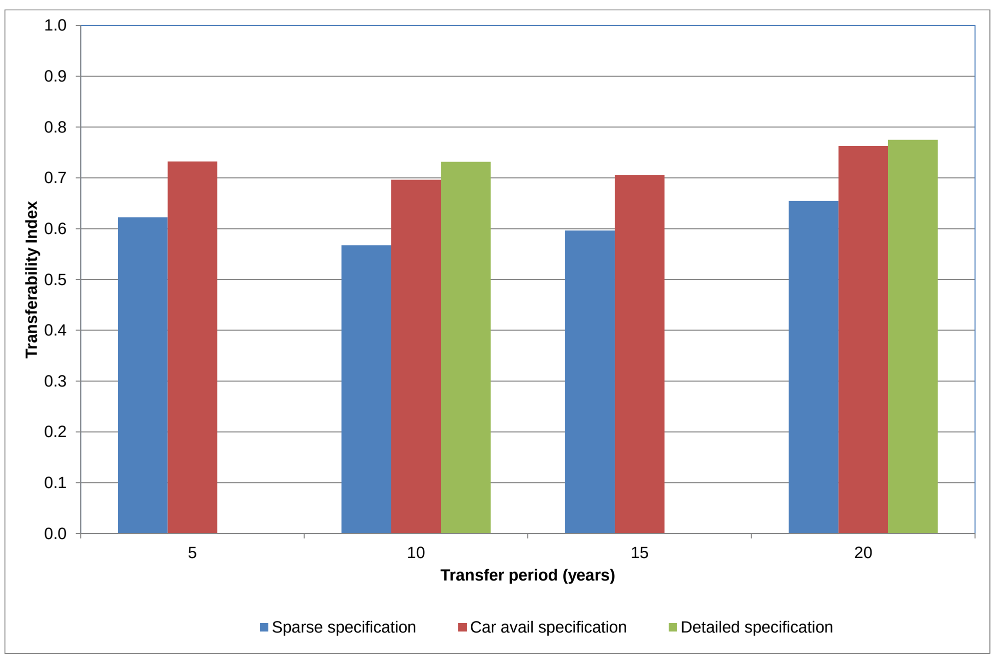

Figure 6.1: Mean TI values by transfer period and model specification

6.2.2 Sydney data

Home–work analysis

Table 6.9 summarises for the Sydney commute models the TI values and the fit of the model in the transfer context, $LL_t(\beta_b)$ for the two possible model transfers.

Table 6.9: TI values, Sydney commute models

Transfer	measure	Model specification			
		Sparse	Car avail	Detailed	Detailed & income
1991 to 2006	TI	0.90	0.91	0.87	0.87
	$LL_t(\beta_b)$	-34,630.7	-34,361.3	-34,376.2	-34,277.2
2006 to 1991	TI	0.81	0.85	0.80	0.82
	$LL_t(\beta_b)$	-30,142.8	-29,887.3	-29,837.2	-29,731.2

For all model specifications the Sydney commute model have a high level of transferability, with at least 80% of the explanatory power of the transfer context model (relative to the reference model). Adding the car availability parameters leads to increases in model transferability, but the addition of further socio-economic terms in the detailed specification, and income segmented cost terms in the detailed & income specification, does not lead to further increases in transferability as measured by the TI.

It should be noted that the decline in TI in the detailed specifications does not necessarily mean that the fit to the transfer data has worsened, in fact as Table 6.9 illustrates the 2006 to 1991 results show that the fit in the transfer context consistently improves with model specification despite the pattern shown by the TI measures. It can be seen from Table 6.2 that the TI can worsen if the *improvement* in fit in the transfer context relative to the base model is lower than the improvement in fit in the base context. This is a limitation of using the TI measure alone to assess the impact of transferability.

Home–other travel analysis

Table 6.10 summarises the TI values calculated for the Sydney home–other travel models.

Table 6.10: TI values, Sydney home–other travel models

Transfer	measure	Model specification Sparse	 Car avail	 Detailed	 Detailed & income
1991 to 2006	TI	0.62	0.73	0.75	0.74
	$LL_t(\beta_b)$	-54,910.4	-54,468.9	-54,084.2	-54,115.6
2006 to 1991	TI	0.15	0.33	0.41	0.41
	$LL_t(\beta_b)$	-49,068.9	-48,650.9	-48,333.8	-48,333.8

The home–other travel models are consistently less transferable than the equivalent commute model, particularly for the four transfers from 2006 back to 1991.

Once again, adding the car availability terms results in a clear increase in model transferability. The addition of further socio-economic terms in the detailed specification leads to some further increase in transferability, but no further improvement is observed when income segmented cost terms are introduced in the detailed & income specification.

Tests have also been undertaken for the three other travel sub-purposes using the detailed specification. Initially these were also undertaken using the TI measure, but a complication is that these were impacted by differences in the fit of the models re-estimated in the transfer context. To allow for a more direct comparison, Table 6.11 summarises the fit of the transferred models.

Table 6.11: TI values, Sydney other–travel sub-purpose transfers

Transfer	Without segmentation	Serve passenger	Personal business	Leisure	Total	Gain in likelihood
1991 to 2006	-54,759.0	-16,742.4	-7,719.1	-29,005.2	-53,466.6	1,292.4
2006 to 1991	-48,347.1	-13,666.4	-7,024.6	-27,421.0	-48,112.1	235.1

It can be seen that the predictions of the three sub-purpose models give a better fit to the transfer data, particularly for the transfers from 1991 to 2006. Thus the tests indicate that segmenting home–other travel into separate sub-purposes gives more transferable models.

6.2.3 Discussion

Overall, the results demonstrate that transferability improves with model specification, consistent with the findings of Parody (1977), Train (1978) and Badoe and Miller (1995a), all of whom found that the transferability of mode choice models improved with model transferability. The implication for analysts is that improving the model specification would be expected to improve the transferability of models, particularly when the improvements are to add car availability terms to the model. This is an important result, because adding additional model terms can make it more time consuming to apply the models in model application.

The Sydney analysis suggests that home–other travel models are less transferable than commute models. However, improved transferability was observed for the Sydney data when home–other travel was segmented into serve passenger, personal business and other travel sub-purposes.

6.3 Predictive measures

Statistical measures of transferability are useful in providing an understanding of the ability of the models to predict the individual level choices observed in the transfer context. However, when models are used in forecasting by definition detailed travel behaviour data is not available in the transfer context, i.e. the future year that is being forecast, and what is important is the ability of the models to predict aggregate changes in mode and trip length. Therefore in this section, the ability of the transferred models to predict the observed changes in mode share and trip length is analysed.

To make the predictive tests, the base models were applied in the transfer context using the transfer data, and the predicted mode shares and tour lengths were calculated. These predicted mode share and tour lengths were then compared to the mode shares and tour lengths observed in the transfer data, and the differences between observed and predicted data were tabulated.

6.3.1 Toronto data

The Toronto analysis has been undertaking using the detailed model specification, the specification that gives the best fit to the base data. Tests have been made using both the 1986 and 2006 base models of the ability of the models to predict the observed changes in mode share and trip length over 10 and 20 year transfer periods. Tables 6.12 and 6.13 compare the predicted and observed changes in mode share and tour length for the 1986 base models.

The overall RMS measures for mode share and tour length were calculated using Equation 6.3 and Equation 6.4.

$$RMS(S) = \sqrt{\frac{\sum_m (S_m^p - S_m^o)^2}{M}} \tag{6.3}$$

$$RMS(T) = \sqrt{\frac{\sum_m (T_m^p - T_m^o)^2}{M}} \tag{6.4}$$

where: m is the mode, with M modes in total

S_m^p and S_m^o are the predicted and observed mode shares

T_m^p and T_m^o are the predicted and observed tour lengths by mode

Table 6.12: Mode share predictions, 1986 base model

Mode	1986 obs	1996 obs	1996 pred	error	2006 obs	2006 pred	error
car driver	67.9%	73.3%	75.7%	2.4%	76.0%	77.2%	1.3%
car passenger	9.4%	9.7%	9.8%	0.1%	8.7%	11.1%	2.4%
local transit	20.3%	14.7%	12.0%	-2.7%	12.7%	9.4%	-3.4%
walk	2.3%	2.3%	2.6%	0.3%	2.6%	2.3%	-0.3%
Total	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%
			RMS	1.8%		RMS	2.4%

Table 6.13: Tour length predictions (km), 1986 base model

Mode	1986 obs	1996 obs	1996 pred	error	2006 obs	2006 pred	error
car driver	34.0	40.1	36.5	-3.6	39.5	38.2	-1.3
car passenger	28.6	33.0	29.3	-3.7	29.7	32.2	2.5
local transit	23.3	25.9	23.5	-2.5	25.7	23.1	-2.7
walk	4.1	4.1	4.0	0.0	4.3	4.1	-0.3
Total	30.6	36.5	33.2	-3.3	36.0	35.3	-0.7
			RMS	2.9		RMS	1.9

The key changes in mode share between 1986 and 1996 are the 5.4% increase in the car driver share, and the 5.7% reduction in the local transit share. The transferred model over-predicts these changes by 2.4% and 2.7% respectively. By 2006, the car driver share has increased by 8.1%, which is over-predicted by just 1.3%, and the local transit share has declined by 7.6%, which is over-predicted by 3.4%.

Overall mean tour lengths increased by 5.9 km between 1986 and 1996, whereas the transferred model only predicts a 2.8 km increase. The observed increases in tour length for car driver, car passenger and local transit are all under-predicted by 2 to 4 km. Observed tour lengths show no further increase between 1996 and 2006, whereas the transferred model predicts a further increase in mean tour length, and consequently overall mean tour lengths are predicted well in 2006. However, the fit at the modal level is less good, in particular local transit tour lengths are predicted to reduce relative to 1986 when in fact they increased by 2.4 km.

Tables 6.14 and 6.15 summarises compares the predicted and observed changes in mode share and tour length for the 2006 base models.

Table 6.14: Mode share predictions, 2006 base model

Mode	2006 obs	1996 obs	1996 pred	error	1986 obs	1986 pred	error
car driver	76.0%	73.3%	73.4%	0.1%	68.0%	64.1%	-3.8%
car passenger	8.7%	9.7%	8.0%	-1.7%	9.4%	7.4%	-2.1%
local transit	12.7%	14.7%	15.7%	1.1%	20.3%	26.0%	5.7%
walk	2.6%	2.3%	2.9%	0.6%	2.3%	2.5%	0.2%
Total	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%
			RMS	1.0%		RMS	3.5%

Table 6.15: Tour length predictions (km), 2006 base model

Mode	2006 obs	1996 obs	1996 pred	error	1986 obs	1986 pred	error
car driver	39.5	40.1	38.5	-1.6	34.0	37.6	3.6
car passenger	29.7	33.0	27.6	-5.4	28.6	27.1	-1.3
local transit	25.7	25.9	27.1	1.2	23.3	27.2	3.8
walk	4.3	4.1	4.2	0.2	4.1	4.3	0.2
Total	36.0	36.5	34.8	-1.7	30.6	33.3	2.6
			RMS	2.9		RMS	2.7

The transferred 2006 model accurately predicts the car driver share in 1996, and also predicts the local transit share to within 1%. However, the car passenger share is predicted to reduce slightly when a small increase is observed, leading to a 1.7% error. The reduction in car driver share to 1986 was over-predicted by 3.8%, and the increase in local transit share was over-predicted by 5.7%. So as per the 1986 base model, the large changes in mode share which occur between 1986 and 1996 are over-predicted.

As noted above, overall tour lengths remain more or less constant between 2006 and 1996, whereas the transferred model predicts a 1.6 km reduction.

6.3.2 Sydney data

The analysis followed the approach developed for the Toronto data, with observed and predicted changes in mode share and tour length over the transfer period investigated. The tests were undertaken using the detailed & income specification models, i.e the best model specifications incorporating variation in cost sensitivity with income band.

Home–work analysis

Table 6.16 and Table 6.17 present the results from the predictive tests made with the 1991 and 2006 base models respectively. In these tables the first set of comparisons compare the predicted modes shares in the transfer context to the shares observed in both the base and transfer contexts, and the second set of comparisons compare the predicted tour lengths in the transfer context to the values observed in both the base and transfer contexts.

Table 6.16: Sydney commute predictive tests, 1991 base

	Mode share				Tour length (km)			
Mode	1991 obs	2006 obs	2006 pred	error	1991 obs	2006 obs	2006 pred	error
car driver	63.2%	65.1%	68.4%	3.2%	32.5	29.6	31.1	1.5
car passenger	9.3%	6.3%	7.8%	1.4%	25.6	21.0	24.3	3.2
train	14.9%	14.2%	10.6%	-3.6%	62.7	51.6	50.3	-1.3
bus	6.2%	8.0%	6.1%	-1.9%	19.7	18.7	17.1	-1.6
bike	0.6%	0.6%	0.5%	-0.1%	12.9	11.4	11.8	0.4
walk	5.4%	5.3%	5.8%	0.5%	4.3	3.1	3.5	0.4
taxi	0.4%	0.4%	0.8%	0.4%	15.1	17.8	25.3	7.5
Total	100.0%	100.0%	100.0%	0.0%	33.8	29.7	30.0	0.3
			RMS	2.0%			RMS	3.3

The models predict the observed changes in mode share only reasonably. While in the author's view the overall RMS is good at 2.0–2.7%, this result is biased by modes with a low share. Both transfers over-predict the observed changes in the car driver share. Given that Section 5.4 found that the car availability parameters have a good level of temporal transferability, one explanation is that the models

Table 6.17: Sydney commute predictive tests, 2006 base

	Mode share				Tour length (km)			
Mode	2006 obs	1991 obs	1991 pred	error	2006 obs	1991 obs	1991 pred	error
car driver	65.1%	63.2%	58.7%	-4.5%	29.6	32.5	31.1	-1.3
car passenger	6.3%	9.3%	7.5%	-1.8%	21.0	25.6	21.4	-4.2
train	14.2%	14.9%	19.5%	4.6%	51.6	62.7	61.7	-1.0
bus	8.0%	6.2%	8.5%	2.3%	18.7	19.7	21.9	2.2
bike	0.6%	0.6%	0.7%	0.1%	11.4	12.9	12.3	-0.5
walk	5.3%	5.4%	4.9%	-0.5%	3.1	4.3	3.7	-0.6
taxi	0.4%	0.4%	0.2%	-0.2%	17.8	15.1	26.4	11.3
Total	100.0%	100.0%	100.0%	0.0%	29.7	33.8	34.1	0.3
			RMS	2.7%			RMS	4.7

over-predict the change in the car driver share because they are under-sensitive to the 84% increase in fuel costs between 1991 and 2006.

The change in overall tour length given by the level of service measures[2] is modelled well by the models (the high RMS is as a result of taxi, but this mode has a very low mode share).

Home–other travel analysis

Table 6.18 and Table 6.19 present the results from the predictive tests made with the 1991 and 2006 base models respectively. Again, the first set of comparisons compare the predicted modes shares in the transfer context to the shares observed in both the base and transfer contexts, and the second set of comparisons compare the predicted tour lengths in the transfer context to the values observed in both the base and transfer contexts.

The observed changes in mode share are predicted more accurately than in the commute model, and in particular the observed change in the car driver share is more accurately predicted, possibly because the home–other travel model is more sensitive to cost changes than the commute model.

[2]as discussed in Section 3.3.2 this is believed to be a result of the changes in the networks, not a real change in tour length

Table 6.18: Sydney home–other travel predictive tests, 1991 base

	Mode share				Tour length (km)			
Mode	1991 obs	2006 obs	2006 pred	error	1991 obs	2006 obs	2006 pred	error
car driver	43.7%	47.0%	48.5%	1.5%	16.7	13.1	18.7	5.6
car passenger	32.5%	29.8%	30.1%	0.2%	19.2	14.4	19.5	5.2
train	2.0%	1.7%	2.3%	0.7%	55.8	46.3	48.5	2.2
bus	2.6%	1.7%	3.1%	1.4%	18.1	11.3	17.4	6.1
bike	1.0%	1.0%	0.9%	-0.1%	8.2	6.0	7.0	1.0
walk	17.8%	18.5%	14.4%	-4.1%	4.2	2.2	3.2	1.0
taxi	0.5%	0.3%	0.8%	0.5%	16.4	12.2	20.5	8.3
Total	100.0%	100.0%	100.0%	0.0%	16.1	11.9	17.3	5.4
			RMS	1.8%			RMS	4.9

Table 6.19: Sydney home–other travel predictive tests, 2006 base

	Mode share				Tour length (km)			
Mode	2006 obs	1991 obs	1991 pred	error	2006 obs	1991 obs	1991 pred	error
car driver	47.0%	43.7%	44.2%	0.5%	13.1	16.7	13.7	-3.1
car passenger	29.8%	32.5%	33.9%	1.4%	14.4	19.2	16.6	-2.6
train	1.7%	2.0%	3.1%	1.1%	46.3	55.8	59.2	3.4
bus	1.7%	2.6%	2.6%	0.0%	11.3	18.1	17.9	-0.2
bike	1.0%	1.0%	1.1%	0.0%	6.0	8.2	7.0	-1.2
walk	18.5%	17.8%	15.0%	-2.8%	2.2	4.2	3.1	-1.1
taxi	0.3%	0.5%	0.2%	-0.2%	12.2	16.4	17.5	1.0
Total	100.0%	100.0%	100.0%	0.0%	11.9	16.1	14.5	-1.5
			RMS	1.3%			RMS	2.1

However, the tour length predictions are less good, particular for the 1991 base model which predicts a 1.2 km increase in tour length when the observed change is a 4.2 km reduction. These results are likely to be a combination of the network changes discussed in Section 3.3.2 and the model predictions, but disentangling the two effects is difficult.

The predictive tests have also been undertaken for the sub-purpose models to investigate whether these models are better able to predict observed changes in mode share and tour length than the total other travel model. Table 6.20 summarises the RMS measures for mode share and tour length obtained when the 1991 base sub-purpose models were transferred to 2006.

Table 6.21 presents the corresponding set of results obtained when the 2006 base

Table 6.20: Sub-purpose predictive tests, 1991 base transferred to 2006

	Without segmentation	Serve passenger	Personal business	Leisure	Mean
Mode share	1.8%	0.6%	1.4%	4.8%	2.3%
Tour length (km)	4.9	3.4	5.0	4.4	4.3

sub-purpose models were transferred to 1991.

Table 6.21: Sub-purpose predictive tests, 2006 base transferred to 1991

	Without segmentation	Serve passenger	Personal business	Leisure	Mean
Mode share	1.3%	1.1%	1.6%	2.7%	1.8%
Tour length (km)	2.1	5.9	3.5	3.6	4.3

On the basis of these results there is no evidence that segmenting home–other travel into separate sub-purpose models results in better predictions of observed changes in mode share and tour length.

6.3.3 Discussion

The mode share and tour length predictions are reasonable, with the models generally predicting the direction of key changes correctly (though in the case of the car mode share, this will be driven principally by higher car availability in later years of data). The Sydney tour length analysis is complicated by the impact of network changes following from the change to the zoning system, and this highlights that if a model is applied to a network that is significantly different from the network used in model application can have a significant impact on the model predictions, and therefore the transferability of the original model.

In both the Toronto and Sydney analyses, the observed increase in car driver share over time is over-predicted by the transferred models. In both cases the increase in share has been accompanied by a significant real terms increase in car costs, and so one explanation is that the models are under-sensitive to the longitudinal change in costs. As Section 5.1.1 highlights, longitudinal income elasticities have been found to be significantly lower than the cross-section values, and it is possible that a similar relationship exists for modal cost changes. An alternative explanation is that the growth in car use has been suppressed by increased congestion and associated parking difficulties, which impacts upon commute travel more than on the other travel purpose. More research would be valuable here to explore these different hypotheses.

6.4 Elasticities

6.4.1 Toronto data

The elasticity tests were undertaken using the detailed model specification. Elasticities were calculated for the 1986, 1996 and 2006 base models, and then the elasticities for the 1996 and 2006 base models were compared to those obtained by transferring the 1986 models.

Table 6.22: Toronto commute model elasticities

Elasticity	Units	1986	1996			2006		
			base	1986 tran	tran/base	base	1986 tran	tran/base
fuel cost	kms	-0.156	-0.113	-0.141	1.244	-0.234	-0.179	0.763
car time	trips	-0.149	-0.095	-0.087	0.914	-0.106	-0.074	0.699
PT fare	trips	-0.280	-0.344	-0.358	1.042	-0.376	-0.309	0.823
PT IVT	trips	-0.780	-0.799	-0.830	1.039	-0.881	-0.912	1.035

Comparison of the 1986 values to base values for 1996 and 2006 shows the elasticities change when the same model specification is estimated on the 1986, 1996 and 2006 datasets. The elasticities from the best fitting model for each year fluctuate noticeably, particularly for the fuel cost kilometrage elasticity. The kilometrage elasticities are impacted by the relative strength of the linear and log cost terms – in a pure log cost model the impact of a uniform 10% increase in cost is to add a constant to the utility of each destination alternative and therefore no destination choice response would be observed. Thus the low fuel cost kilometrage elasticity in the 1996 model can be explained by the fact that the linear cost term is smaller in magnitude than in the 1986 and 2006 models. Thus an important point is that the elasticities calculated are impacted by the particular model results as well as any changes in sensitivity in the population.

A general pattern is that the difference between the transfer elasticity and the base elasticity is higher over the longer 20 year transfer to 2006 than over the 10 year transfer to 1996. While this result is intuitive, the analysis of the transferability index presented in Section 6.2 did not identify a pattern of reducing transferability with increased transfer period. No consistent pattern of divergence between the base and transferred elasticities emerges, such as higher or lower sensitivity in the transferred models.

6.4.2 Sydney data

The Sydney elasticity tests were undertaken using the detailed & income model specification which incorporates variation in cost sensitivity with income. Elasticities were calculated for both the 1991 and 2006 base models, and then the elasticities for the 2006 base models were compared to those obtained by transferring the 1991 models to 2006. Table 6.4.2 summarises the results for commute.

Table 6.23: Sydney commute model elasticities

Elasticity	Units	1991	2006		
			base	1991 tran	tran/base
Fuel cost	kms	-0.15	-0.16	-0.18	1.12
Car time	tours	-0.27	-0.25	-0.11	0.45
PT cost	tours	-0.38	-0.32	-0.33	1.05
PT IVT	tours	-0.50	-0.77	-0.54	0.70

The correspondence between the base and transfer cost elasticities in 2006 is better than in the Toronto models. However, the transferred model gives lower time elasticities than the 2006 base model. It seems likely that the time elasticities will be impacted by the reductions in mean trip distance, and hence mean travel time, that result from the move to a more detailed zoning system in 2006 (as discussed in Section 3.3.2).

Table 6.4.2 summarises the results for home–other travel.

Table 6.24: Sydney home–other travel model elasticities

Elasticity	Units	1991	2006		
			base	1991 tran	tran/base
Fuel cost	kms	-0.02	-0.03	-0.02	0.76
Car time	tours	-0.14	-0.10	-0.06	0.57
PT cost	tours	-0.33	-0.27	-0.23	0.86
PT IVT	tours	-0.47	-0.79	-0.46	0.58

There are larger differences between the 2006 base elasticities and those obtained by transferring the 1991 models to 2006 than were observed for commute, with a general pattern whereby the transferred model under-predicts the 2006 base sensitivity. It was observed in Section 3.3.2 that home–other travel is more strongly impacted by the change in zoning system because mean tour lengths are lower, and therefore it is not possible to draw any wider conclusions from this result.

Elasticity tests were also undertaken for the home–other sub-purposes. These tests were restricted to the fuel cost kilometrage and PT IVT tests to restrict the number of tests run. Table 6.25 summarises the results for the fuel cost kilometrage tests.

For both the 1986 base and 2006 base values, there is considerable variation in the elasticities between the different sub-purposes, through the elasticity values are low in all cases due to the log cost formulation used in the model. The transfer elasticities are consistently lower than the 2006 base values, but again the impact of the change in zoning system is likely be influence this result.

Table 6.25: Sydney home–other travel sub-purpose fuel cost kilometrage elasticity tests

Purpose	1991	2006		
		base	1991 trans	tran/base
Without segmentation	-0.025	-0.029	-0.022	0.76
Serve passenger	-0.009	-0.023	-0.008	0.33
Personal business	-0.037	-0.035	-0.031	0.90
Other travel	-0.033	-0.047	-0.023	0.50

Table 6.26 summarises the results for the PT IVT elasticity tests.

Table 6.26: Sydney home–other travel sub-purpose PT IVT trip elasticity tests

Purpose	1991	2006		
		base	1991 trans	tran/base
Without segmentation	-0.472	-0.788	-0.458	0.58
Serve passenger	-0.439	-0.817	-0.402	0.49
Personal business	-0.529	-0.766	-0.567	0.74
Other travel	-0.481	-0.732	-0.455	0.61

There is less variation between sub-purposes in the base elasticities for the PT IVT trip elasticity tests. Once again the change in zoning system is likely to be a key factor in the lower sensitivity obtained when the 1986 model is transferred to 2006.

6.4.3 Discussion

A key point that the elasticity comparison highlights is that the elasticities calculated from a given model are specific to the model results, and in particular in these models are impacted by the relative strength of the linear and log cost terms. This makes it difficult to draw firm conclusions about how well the transferred models replicate any observed changes in sensitivity over time.

In general the transferred models give reasonable similar results to the base models. No pattern of systematic under- or over-prediction of sensitivity emerged from the Toronto analysis, and the impact of zoning change makes it difficult to draw out conclusions from the Sydney analysis. It is noteworthy that while the analysis of differences in individual parameter values presented in Section 5.4 suggested the in-vehicle time parameters to be more transferable than the cost parameters, this pattern is not repeated in the elasticity measures.

Further research would be valuable on this issue to try to better disentangle changes in model sensitivity from the evolution of changes in the underlying sensitivity of travellers to cost and time changes. An issue here is the relative lack of evidence on how, if at all, elasticities are actually changing over time. For example, Dunkerley (2014), in a review of elasticity values relevant to the UK context, found limited evidence on changes in car cost and car time elasticities over time.

Chapter 7

Pooled models

This chapter presents results from models that investigate model transferability by pooling different years of the Toronto data.

Section 7.1 presents partial transfer models, whereby the base model is transferred be estimating scale parameters in the transfer context. Repeating this approach for different transfer years allows analysis of how the transfer scale parameters vary over time and between parameter type.

Section 7.2 presents models that are estimated by pooling over different years of data. The analysis investigates whether pooling data in this way can yield models which are better at predicting behaviour in the transfer context than using data from the most recent year alone.

The chapter concludes in Section 7.3 with a summary of the findings from the pooled model analysis.

7.1 Partial transfer models

A number of authors in the spatial transfer literature have employed a partial transfer approach whereby different groups of utility terms are transferred from the base to transfer context by estimating scale parameters using some information from the transfer context. For example, Koppelman and Wilmot (1982) transferred mode choice models from one area of Washington D.C. to another, Gunn et al. (1985) transferred mode-destination choice models between adjacent regions of the Netherlands, Daly (1985) transferred mode choice models from Grenoble to Nantes, and Gunn and Fox (2005) used the partial transfer approach to transfer national models for the Netherlands to four regions of the Netherlands.

When models are used in forecasting, information is not available in the transfer context. However, the partial transfer approach can be used to make assessments of transferability using historical data collected at different points in time. The Toronto data has been used for this analysis because data is available collected at four different points in time over a 20 year period.

Changes in the scale of the following groups of utility parameters has been investigated:

- cost terms
- level-of-service (LOS) terms
- socio-economic (SE) terms
- mode and destination constants

These groupings were used drawing on the findings from the literature review and the analysis presented in Section 5.4 that parameters in these different groups exhibit different degrees of temporal transferability.

By transferring a given base model to each other year of data, the evolution in the scale parameters over time can be investigated. Two sets of tests have been undertaken, all using model specification B so that the models can be transferred to 2001. First, 1986 base models have been transferred to 1996, 2001 and 2006. Second, 2006 base models have been transferred to 2001, 1996 and 1986.

The utilities for the base models were detailed earlier in Section 4.2.3. The utilities for the partial transfer models can then be written as follows:

$$V^t_{md} = \mu^t_{cost} \sum_e \beta^b_{cost,e} x^t_{cost,e} \; + \; \mu^t_{LOS} \sum_f \beta^b_{LOS,f} x^t_{LOS,f} \; + \\ \mu^t_{SE} \sum_g \beta^b_{SE,g} x^t_{SE,g} \; + \; \mu^t_{const} \sum_h \beta^b_{const,h} x^t_{const,h} \quad (7.1)$$

where: μ^t_{cost} is the scale parameter estimated for the e cost parameters
μ^t_{LOS} is the scale parameter estimated for the f LOS parameters
μ^t_{SE} is the scale parameter estimated for the g socio-economic parameters
μ^t_{const} is the scale parameter estimated for the h constants
$\beta^b_{cost,e}$, $\beta^b_{LOS,f}$, $\beta^b_{SE,g}$ and $\beta^b_{const,h}$ are the base parameters
$x^t_{cost,e}$, $x^t_{LOS,f}$, $x^t_{SE,g}$ and $x^t_{const,h}$ is the transfer context data

The results from these tests are summarised in Table 7.1 and Table 7.2. The t-ratios of the scale parameters are given in brackets and define the significance of the scale parameter relative to a value of one. The tables also present the Transferability Indices (TI) defined in Equation 2.21 for both the partial transfer models, and for the equivalent naïve transfers of the base model (i.e. transferring the base parameters without adjustment, which is equivalent to a partial transfer model in which all of the scale parameters are constrained to a value of 1).

Examining the results from the partial transfers of the 1986 model, the cost terms

Table 7.1: Partial transfers, 1986 base, specification B

	1996		2001		2006	
μ^t_{cost}	0.879	(11.4)	0.736	(21.1)	1.192	(17.0)
μ^t_{LOS}	0.814	(45.7)	0.892	(31.1)	0.898	(24.2)
μ^t_{SE}	1.074	(3.7)	1.157	(9.2)	0.976	(1.2)
μ^t_{const}	0.984	(2.0)	0.927	(9.9)	1.072	(9.4)
TI (partial transfer)	0.970		0.882		0.857	
TI (naïve transfer)	0.691		0.716		0.675	

Table 7.2: Partial transfers, 2006 base, specification B

	2001		1996		1986	
μ^t_{cost}	0.664	(28.1)	0.777	(19.2)	0.896	(7.6)
μ^t_{LOS}	0.962	(9.9)	0.910	(20.1)	1.126	(22.0)
μ^t_{SE}	1.184	(12.9)	1.013	(0.8)	0.962	(2.3)
μ^t_{const}	0.884	(16.8)	0.863	(19.3)	0.864	(18.2)
TI (partial transfer)	0.875		0.852		0.879	
TI (naïve transfer)	0.784		0.705		0.762	

have a good level of transferability to the 1996 and 2006 data (i.e. the scale parameters have values close than one), but the low scale for 2001 demonstrates that their transferability to the 2001 data is not as good. The LOS terms are more stable, with the scale of the parameters reduced by between 10% and 20%. The socio-economic parameters have a high degree of transferability, with scale parameters relatively close to one for each of the transfer years. Finally, the constants also retain a good level of transferability over time, with scale parameters not too far from one. These results show some discrepancies relative to the comparisons of changes in individual model parameters by year relative to the 1986 base model presented in Section 5.4. In those comparisons, the LOS parameters were most transferable on average, and the constants least.

The TI values for the partial transfers of the 1986 model demonstrate that a noticeable improvement in transferability is achieved relative to naïve transfers.

Analysing the results from the partial transfers of the 2006 base model, it can be seen that the cost terms have the lowest scale values, highlighting the relatively low transferability of the cost terms. The model constants have the second lowest scale values in all three partial transfers. The LOS and socio-economic parameters have the scale values closest to one and therefore are more transferable over time. The patterns of variation between parameter group are generally consistent with the comparisons of individual parameters relative to the 1986 base model presented in Section 5.4.

The TI values for the partial transfers of the 2006 model demonstrate that a noticeable improvement in transferability is achieved relative to naïve transfers, but the improvements in TI values are not as large as those obtained from the partial transfers of the 1986 model.

In summary, while the partial transfer approach results in improved transferability measures relative to naïve transfers, the patterns of change in the individual scale parameters over time do not indicate any consistent patterns where one of the utility groups steadily increases or decreases in scale over time.

7.2 Pooled models

If household interview, level-of-service and attraction data exists for different points in time, then the question arises as to whether it is best to pool the different datasets in some way, or simply follow the conventional approach of using the most recent data to forecast future behaviour. This question is particularly relevant in the current economic climate, where due to restrictions on government spending there may be pressure to cut sample sizes for household interviews.

Badoe and Wadhawan (2002) estimated mode choice models by pooling 1964 and 1986 data for the Toronto area, and compared the ability of these models to predict 1991 travel choices to the predictive performance of models estimated using the more recent 1986 data only. Different specifications for the pooled models were tested, ranging from naïve pooling to models with separate mode constants, level-of-service parameter scales and socio-economic parameter scales by year. The models with separate constants and scales by year gave better a better fit to the disaggregate 1991 mode choices than the naïve pooled model, but none of the pooled models gave as good a fit as the 1986-only model. However, using an aggregate measure of predictive performance across different spatial segments, the best pooled model performed slightly better than the 1986-only model. Sanko (2014a) investigated the ability of models developed from 1971, 1981 and 1991 data to explain 2001 mode choices in the Nagoya region of Japan. He found that a model estimated from the most recent 1991 data better predicted the 2001 mode choices than a pooled model with different constants and LOS and socio-economic scale parameters by year. Thus, despite using estimating pooled models using separate scale parameters and constants by year, other researchers have found using only the most recent data gives the best fit to the transfer data for mode choice models.

As the experimental approach relies on estimating a pooled model from two years of data, and investigating the ability of the pooled model to predict behaviour in a third transfer context, the Toronto data was once again used for this analysis.

7.2.1 Model specification

Badoe and Wadhawan (2002) found that pooled models yielded better predictive performance if separate constants and scale parameters were used for different years of data. A number of pooled model specifications were tested to investigate whether the same result is observed for the Toronto home-work mode-destination models. A total of five pooled models have been estimated by pooling the 1986 and 1996 data. The pooled models all use specification B.

- Pooled 1: naïve pooling
- Pooled 2: 1986 data scaled relative to 1996 data
- Pooled 3: 1986 data scaled relative to 1996 data, mode constants by year
- Pooled 4: 1986 data scaled relative to 1996 data, separate scaling by utility group
- Pooled 5: 1986 data scaled relative to 1996 data, separate scaling by utility group, mode constants by year

The 1986 and 1996 data has been pooled by taking the full 1986 sample, and 50% of the 1996 sample. This allows investigation of the transferability of models estimated by pooling a large old dataset with a smaller more recent dataset to be compared to the transferability of models estimated from a large recent dataset alone. In the pooled model, the utilities for the 1986 and 1996 data can be written as follows:

$$\begin{aligned} V_{md}^{86} = \mu_{cost}^{86} \sum_{e} \beta_{cost,e}\ x_{cost,e}^{86}\ +\ \mu_{LOS}^{86} \sum_{f} \beta_{LOS,f}\ x_{LOS,f}^{86}\ + \\ \mu_{SE}^{86} \sum_{g} \beta_{SE,g}\ x_{SE,g}^{86}\ +\ \mu_{const}^{86}(\beta_{ASC}^{86}\ +\ \sum_{h} \beta_{const,h}\ x_{const,h}^{86}) \end{aligned} \tag{7.2}$$

$$\begin{aligned} V_{md}^{96} = \sum_{e} \beta_{cost,e}\ x_{cost,e}^{96}\ +\ \sum_{f} \beta_{LOS,f}\ x_{LOS,f}^{96}\ + \\ \sum_{g} \beta_{SE,g}\ x_{SE,g}^{96}\ +\ \beta_{ASC}^{96}\ +\ \sum_{h} \beta_{const,h}\ x_{const,h}^{96} \end{aligned} \tag{7.3}$$

In model 1, the four scale parameters $\mu_{cost}^{86}, \mu_{LOS}^{86}, \mu_{SE}^{86}$ and μ_{const}^{86} are all constrained to one. Furthermore, $\beta_{ASC}^{86} = \beta_{ASC}^{96} \forall m$.

In model 2, the four scale parameters $\mu_{cost}^{86}, \mu_{LOS}^{86}, \mu_{SE}^{86}$ and μ_{const}^{86} are replaced by a single scale parameter μ^{86}, and $\beta_{ASC}^{86} = \beta_{ASC}^{96} \forall m$.

In model 3, a single scale parameter μ^{86} is estimated but separate mode constants are estimated by year.

In model 4, separate scale parameters are estimated by utility group but $\beta^{86}_{ASC} = \beta^{96}_{ASC} \forall m$.

Finally, in model 5 the utility functions given in Equations 7.2 and 7.3 are estimated directly.

The same set of five pooled models has been estimated by combining the 1996 and 2006 data. The data has been pooled by using 50% of the 1996 data and the full 2006 sample, which are then used to predict behaviour in the 1986 transfer context. The utilities for the 1996 data are given by Equation 7.3. The utilities for the 2006 data are given by the following equation:

$$\begin{aligned} V^{06}_{md} = \mu^{06}_{cost} \sum_e \beta_{cost,e}\ x^{06}_{cost,e}\ +\ \mu^{06}_{LOS} \sum_f \beta_{LOS,f}\ x^{06}_{LOS,f}\ + \\ \mu^{06}_{SE} \sum_g \beta_{SE,g}\ x^{06}_{SE,g}\ +\ \mu^{06}_{const}(\beta^{06}_{ASC}\ +\ \sum_h \beta_{const,h}\ x^{06}_{const,h}) \end{aligned} \tag{7.4}$$

7.2.2 Model transferability

The full parameter results from the Pooled models are presented in Appendix B.

The transferability of the pooled 1986 & 1996 models to 2001 and 2006 has been compared to that obtained from the specification B model estimated from the *full* 1996 sample alone. The pooled models are applied using the 1996 parameters, i.e. the utilities are not scaled by the 1986 scale parameters and the 1996 mode constants are used. Table 7.3 and Table 7.4 compare the log-likelihood values obtained when the pooled and 1996 models are used to predict the 2001 and 2006 mode-destination choices, and also present the corresponding TI measures.

Table 7.3: Pooled 1986 & 1996 models transferred to 2001

	1996 model	Pooled 1 Naive pooling	Pooled 2 Overall scale	Pooled 3 Overall scale ASCs by year	Pooled 4 Scale by util group	Pooled 5 Scale by util group, ASCs by year
$LL_{01}(\beta_{96})$	-477,901.4	-478,790.2	-478,616.7	-477,401.4	-477,421.2	-477,441.9
gain in LL	n/a	-888.8	-715.3	500.0	480.2	459.4
TI	0.781	0.689	0.707	0.833	0.831	0.829

Table 7.4: Pooled 1986 & 1996 models transferred to 2006

	1996 model	Pooled 1 Naive pooling	Pooled 2 Overall scale	Pooled 3 Overall scale ASCs by year	Pooled 4 Scale by util group	Pooled 5 Scale by util group, ASCs by year
$LL_{06}(\beta_{96})$	-415,454.1	-415,090.6	-415,531.7	-414,893.3	-414,788.2	-414,891.6
gain in LL	n/a	363.5	-77.6	560.9	665.9	562.5
TI	0.570	0.631	0.557	0.664	0.682	0.665

For transfers to 2001, the Pooled 3, 4 and 5 models explain the 2001 mode-destination choices better than the 1996 model. As would be expected, when a different scale is estimated for the 1986 data in Pooled 2 the transferability of the pooled model improves, and there is a substantial improvement in Pooled 3 when separate mode constants are estimated for each year of data. Comparing Pooled 2 and Pooled 4, scaling the 1986 terms separately by the four groups of utility terms leads to a further improvement in model transferability. However, estimating separate mode constants by year of data in Pooled 5 actually results in a slight loss in transferability relative to Pooled 4.

For transfers to 2006, four of the five pooled models better explain the 2006 mode-destination choices than the 1996 model. Consistent with the transfers to 2001, the best model fit is obtained from model Pooled 4 which incorporates scaling by utility group but not separate ASCs by year. However, comparison of

Pooled 2 and Pooled 3 shows estimating separate mode constants by year gives an improvement in fit.

The pooled 1996 and 2006 models have been used to predict the choices observed in the 1986 data, and the fit to the 1986 data compared to that achieved by applying the specification B model estimated from the full 1996 sample. When the pooled models are applied in the 2006 context, the 1996 mode constants are used and the 2006 scale parameters are not applied. Table 7.5 compares the log-likelihood and TI measures obtained from the 1996-only model and the five pooled model specifications.

Table 7.5: Pooled 1996 & 2006 models transferred to 1986

	1996 model	Pooled 1 Naive pooling	Pooled 2 Overall scale	Pooled 3 Overall scale ASCs by year	Pooled 4 Scale by util group	Pooled 5 Scale by util group, ASCs by year
$LL_{86}(\beta_{96})$	-308,674.2	-308,277.8	-308,854.2	-308,737.2	-308,861.6	-308,756.2
gain in LL	n/a	396.4	-180.0	-63.1	187.5	-82.0
TI	0.783	0.855	0.750	0.771	0.748	0.768

For transfers to 1986, only the Pooled 1 model which pools the 1996 and 2006 data naïvely gives a better fit the 1986 data than the 1996-only model. Comparison of Pooled 2 and Pooled 3, and of Pooled 4 and Pooled 5, demonstrates the estimating separate mode constants by year and using the more recent constants in forecasting consistently improves model transferability.

It is noteworthy that for five of the six comparisons of the impact of estimating the constants by year (comparisons of Pooled 2 & Pooled 3 and comparisons of Pooled 4 & Pooled 5) the transferability of the pooled model is improved by estimating the constants separately by year. Chingcuanco and Miller (2012) estimated pooled vehicle ownership models for large urban centres in Ontario incorporating both varying constants and varying scales, and they found that temporal variation was predominately due to differences in the constants rather than differences in overall model scale.

7.2.3 Predictive measures

To test the ability of the transferred models to predict the aggregate shares and tour lengths by mode, RMS measures have been calculated for each of the model transfers to calculate the average error in the predictions at the modal level. The RMS measures have been calculated using Equation 6.3 and Equation 6.4. The results for the transfers to 2001 are presented in Table 7.6, and those for transfers to 2006 are presented in Table 7.7. The measures for 2001 exclude walk, because the walk alternative in the 2001 data is walk and cycle combined, which results in differences in mode shares and trip lengths relative to a pure walk mode.

Table 7.6: Pooled 1986 & 1996 models transferred to 2001 RMS measures

	1996 model	Pooled 1 Naïve pooling	Pooled 2 Overall scale	Pooled 3 Overall scale ASCs by year	Pooled 4 Scale by util group	Pooled 5 Scale by util group, ASCs by year
Mode share	1.36%	0.96%	1.37%	0.90%	1.30%	1.31%
Tour length (km)	3.82	4.26	4.67	2.99	2.67	3.01

Table 7.7: Pooled 1986 & 1996 models transferred to 2006 RMS measures

	1996 model	Pooled 1 Naïve pooling	Pooled 2 Overall scale	Pooled 3 Overall scale ASCs by year	Pooled 4 Scale by util group	Pooled 5 Scale by util group, ASCs by year
Mode share	1.26%	0.94%	1.29%	1.13%	0.95%	0.98%
Tour length (km)	5.06	2.98	4.27	4.70	4.37	4.73

For the 2001 transfers, all the pooled models except Pooled 2 predict mode share better than the 1996 only model. Pooled models 3, 4 and 5 predict the 2001 tour lengths better than the 1996 model.

For the 2006 transfers, again all the pooled models except Pooled 2 predict mode share better than the 1996 model. All of the pooled models predict tour lengths better than the 1996 model, though consistent with mode share the best predictions are given by the Pooled 1 model which pools the 1986 and 1996 data naïvely.

Table 7.8: Pooled 1996 & 2006 models transferred to 1986 RMS measures

	1996 model	Pooled 1 Naïve pooling	Pooled 2 Overall scale	Pooled 3 Overall scale ASCs by year	Pooled 4 Scale by util group	Pooled 5 Scale by util group, ASCs by year
Mode share	2.11%	2.35%	3.04%	1.64%	2.45%	1.70%
Tour length (km)	4.47	2.59	3.95	4.31	4.23	4.33

Only Pooled models 3 and 5, with separate mode shares by year, give better predictions of mode share than the 1996 only model. By contrast, the best prediction of tour lengths is given by the Pooled 1 model, and the other four pooled models perform only slightly better than the 1996-only model.

Overall, although the results are somewhat mixed the recommendation when working with pooled data is that separate scales are estimated by utility group and separate mode constants are estimated by year, with only the more recent constants used to forecast future behaviour.

7.3 Summary

The transfer scaling analysis presented in Section 7.1 sought to investigate model transferability by transferring the base models to the transfer context through the estimation of scale parameters applied to particular parameter groups. The parameter groups used were consistent with those used successfully in Section 5.4 to investigate differences in the transferability of individual parameters.

While the variation in the transfer scale parameters between parameter groups was broadly consistent with the analysis of differences in individual parameters presented in Section 5.4, the variation in the parameters between years did not identify any pattern whereby particular parameter groups increased or reduced in scale with time. While this is consistent with the findings for overall model transferability presented in Section 6.2.1, it does mean that this particular analysis was less insightful than expected.

A possible contribution to the result is that individual parameters may reduce or increase in magnitude, when grouped together these differences may tend to balance out. For example, while Section 5.4 highlighted that the mean change in the constants is higher than that for other parameter groups this did not translate into scale parameters for the constants in the partial transfer analysis that were further from a value of 1 than those for other parameter groups.

Clearer conclusions emerged from the pooled analysis presented in Section 7.2. If data is available from multiple years for model development, then pooling over different years can give more transferable models compared to using data from the most recent available year alone. This is best done by scaling the older data to account for differences in scale over time, and by estimating separate mode constants by year with the most recent constants used for forecasting. This approach may be particularly useful when a larger older survey is available to supplement a smaller more recent survey.

Chapter 8

Random taste heterogeneity models

This chapter presents an investigation into whether accounting for random taste heterogeneity in the Toronto commute models results in improvements in model transferability.

Section 8.1 introduces the analysis, including discussion of some of the difficulties in estimating mode-destination models of this type.

Section 8.2 describes how random taste heterogeneity has been introduced into the model specification s through the introduction of symmetrical triangularly distributed parameters.

Section 8.3 presents the results for models incorporating random taste heterogeneity that have been estimating using the 1986 and 2006 datasets.

Section 8.4 summarises the analysis that was undertaken to investigate the transferability of the 1986 and 2006 models incorporating random taste heterogeneity, including comparison of the results obtained in comparable model specifications that did not incorporate random taste heterogeneity.

Finally, Section 8.5 presents a summary of the analysis.

8.1 Introduction

As discussed in Section 2.1.3, there has been much work in recent years to develop mixed logit models that are able to reflect heterogeneity in individual's tastes. Random taste heterogeneity models can yield significant improvements in model fit relative to multinomial and nested logit forms, and Bhat (1998) has demonstrated that the inclusion of distributed parameters can have a significant impact on the elasticities of models of intercity mode choice.

Random taste heterogeneity models present complications for model estimation because no closed form solution exists for the likelihood function. An approach that is often adopted to estimate the models is to use simulation. For each observation, multiple draws are made from the underlying distribution of the distributed parameters in order to simulate the parameter distributions. Typically at least 100 draws are made per individual, and making these multiple draws leads to significant increases in estimation run times because the choice probabilities need to be calculated separately for each of the draws for each individual. The distributed nature of the parameters also needs to be considered in model application, either by making multiple draws per observation, or for models applied to large samples by using a Monte-Carlo approach to select a value from the parameter distribution for each observation.

Multinomial and nested logit models of mode-destination choice already have relatively long run times because of the large number of alternatives that are represented. Furthermore, if the models are implemented using a sample enumeration approach, the models are applied for a number of different segments which define the different socio-economic terms in the model. Given these issues, to date to the author's knowledge mixed logit models of simultaneous mode-destination choice have not been used in an application system. However, as computing power continues to improve the potential to use mixed logit mode-destination models increases.

The analysis presented in Chapters 5 and 6 demonstrated that improving the model specification of nested logit models by adding terms to account for variation in tastes across different socio-economic groups. The analysis presented in this chapter investigates whether mixed logit models that take account of random taste heterogeneity yield further improvements in transferability relative to comparable multinomial model specifications. This addresses the important question as to whether the improvements in base year model fit that random taste heterogeneity specifications can deliver yields models that are better at forecasting changes in behaviour over time.

The random taste heterogeneity models have been developed using the Toronto TTS data that is described in Section 3.2, and using the Toronto models presented in Section 4.2.2 as a starting point. The Toronto data was used rather than the Sydney data because it allowed assessments over a 20 year transfer period, compared to 15 years with the Sydney data.

8.2 Model specification

The starting point for the mixed logit model specifications was the detailed specification of the Toronto commute model described in Section 4.2.2.

To reduce model run times as far as possible, the models were estimated from a sample of the full set of destination alternatives, a process termed *destination sampling*. However, the theory used to justify destination sampling only applies to multinomial logit models (Ben-Akiva and Lerman, 1985). Therefore, the model tests were using multinomial logit models with modes and destination alternatives constrained to be at the same level. The destination sampling approach used is documented in Appendix D. It should be noted that it has yet been proved that the sampling theory holds for models that incorporate random taste heterogeneity, but because of the problem size limits in the estimation software it was necessary to work with models estimated using sampling.

Building on previous work, randomly distributed parameters for both cost and in-vehicle time (IVT) were tested. For example, Bhat (1998) developed models of intercity mode choice for travel between Toronto and Montréal incorporating both log-normally distributed cost and IVT parameters; however only for IVT was a significant log-normal parameter identified. Daly and Carrasco (2009) developed mode-destination choice models with both cost and IVT parameters using both normal and log-normal distributions; in most cases distributed parameters were added to either cost or time but not both, however in one case it was possible to estimate both effects.

The distributed parameters have been estimated using ALOGIT, which uses an error components specification, where for symmetrical random terms the parameters β are decomposed into a mean effect α and a vector of random effects γ:

$$U_{nj} = \alpha\, x_{nj} + \gamma\, y_{nj} + \varepsilon_{nj} \tag{8.1}$$

where: x_{nj} and y_{nj} are vectors of observed variables relating to alternative j
α is a vector of fixed parameters
γ is a vector of distributed random terms with zero mean

ε_{nj} is iid extreme value

For the subset of terms where distributed parameters are estimated, $x_{nj} = y_{nj}$. For all other terms $y_{nj} = 0$ and only the fixed parameter α is estimated. Tests have been undertaken estimating γ terms for cost, car time and PT in-vehicle time.

Different assumptions were made about the distribution of the random terms. The initial model testing was undertaken using normally distributed parameters. However, as Hess et al. (2005) highlights, the unbounded nature of the normal distribution means that using it assumes both positive and negative values for the parameter whatever the sign of the mean value is. This is problematic for cost and IVT sensitivity, which are expected to be negative, i.e. increasing cost and time would be expected to reduce utility. Other specifications for the random parameters are possible. Hensher (2003) describes the use of normal, triangular, uniform and log-normal distributions. While there are limitations with the log-normal distribution – specifically the long tail on the unbounded side and problems achieving convergence (Hess et al., 2005) – it ensures that cost sensitivity is always negative, and further it would allow an investigation of whether assuming cost sensitivity in Toronto has an asymmetric distribution gives a better fit to the data. For example, Hulchanski et al. (2007) highlighted significant increases in income polarisation in Toronto between 1970 and 2005.

Unfortunately, software difficulties prevented tests with the log-normal distribution. Therefore later model tests were undertaken using triangularly distributed parameters in place of normally distributed parameters because in a triangular distribution the range is finite. The triangular distribution was generated using random terms taking the range -1 to 1 with zero mean:

$$T[-1,1] = U_1[0,1] + U_2[0,1] - 1 \tag{8.2}$$

where: $T[-1, 1]$ is a triangular distribution taking the range -1 to 1 with zero mean

$U_1[0, 1]$ is a uniform distribution taking the range 0 to 1

$U_2[0, 1]$ is an independent uniform distribution taking the range 0 to 1

The subtraction of one in Equation 8.2 gives a distribution with zero mean that ranges from -1 to 1. This means that the term can be used to estimate a spread parameter that defines the range of the triangular distribution around the mean sensitivity for the random term. In some models it was necessary to constrain the range to be equal to the mean to ensure that the distribution always gave negative cost or time sensitivity.

To estimate the random terms, repeated draws are made for each individual to simulate the parameter distribution. An issue with these runs was that limits on the problem size that it is possible to represent in the estimation software meant that no more than 100 draws could be used for the 1986 data, and no more than 90 for the 2006 data. Given these limitations, Halton draws were used (Halton, 1960). The use of Halton draws ensures more uniform coverage of the 0–1 space, which is particularly important when working with a low number of draws.

A potential issue with using Halton sequences for problems with higher numbers of random terms is that the individual Halton sequences used for each random term can be highly correlated. However, the mixed logit models described in this chapter have at most three random terms and so this is not an issue for these models (Bhat, 2003).

8.3 Model results

The random taste heterogeneity specification was developed on the 1986 data. Initially, four triangularly distributed parameters were tested on the linear cost, log cost, car time and transit in-vehicle time parameters. However, the terms on the log cost and transit in-vehicle time parameters were not significant and so the final model specification incorporates triangularly distributed linear cost and car time parameters only.

Table 8.1 summarises the impact of adding the triangular cost and car time terms on the fit to the data and on the other model parameters. It was necessary to constrain the range of the triangular term for cost to be equal to the mean value to ensure that cost sensitivity remained negative across the whole range of the parameter distribution. The changes in the other model parameters (i.e. the non-random terms) have been analysed by calculating the mean change in parameter value using the REM measure given in Equation 2.26.

Table 8.1: Toronto random taste heterogeneity results, 1986

Model	MNL spec. C		Plus distrib. parameters	
Fit	-285,610.7		-285,499.1	
Gain			111.6	
Cost	-0.0010	-12.7	-0.0015	-17.7
CostTri			0.0015	n/a
LogCost	-0.300	-23.6	-0.176	-10.9
CarTime	-0.033	-77.6	-0.037	-65.4
CarTimeTri			0.035	21.7
Other level of service terms			REM = 0.023	
Constants			REM = 0.371	
Socio-economics			REM = 0.033	

The addition of the two distributed parameters leads to a significant gain in log-likelihood. The mean magnitude of the linear cost term increases relative to the model without distributed parameters, and it can be seen that the log-cost term reduces in magnitude and significance. The mean value of car time term increases only slightly relative to the model without distributed parameters.

The REM measures for changes in the non-random model terms show that the level of service and socio-economic terms changes only slightly when the distributed parameters are added. The constants show larger changes, however this result is strongly impacted by changes in the walk mode constant. A full comparison of the two sets of model results is provided in Table B in Appendix B.

When the equivalent mixed logit model specification was estimated on the 2006 data, the log cost term was insignificant and was therefore dropped from the model with random parameters. Table 8.2 summarises the impact of adding the triangular cost and car time terms on the fit to the data and on the other model parameters.

Table 8.2: Toronto mixed logit results, 2006

Model	MNL spec. C		Plus distrib. parameters	
Fit		-388,455.2		-388,320.9
Gain				134.0
Cost	-0.0012	-21.2	-0.0016	-32.4
CostTri			0.0016	n/a
LogCost	-0.255	-16.6	-0.176	-10.9
CarTime	-0.031	-68.8	-0.034	-75.1
CarTimeTri			0.002	26.2
Other level of service terms			REM = 0.015	
Constants			REM = 0.436	
Socio-economics			REM = 0.007	

The addition of the two triangular terms leads to a significant gain in log-likelihood despite the loss of the log cost parameter. The mean values of the linear cost and car time parameters are essentially unchanged when the distributions are introduced. Consistent with the 1986 results, it was necessary to constrain the cost distribution to ensure it was correctly signed across the range of possible values. However, the distribution for the car time parameter shows noticeably less spread than the 1986 results.

The REM parameters show the mean impact of the introduction of the distributed parameters terms on the other level of service parameters is small, as is the impact upon the socio-economic terms. However, much larger differences are observed to the mode constants, and as per the 1986 results the largest change is observed for the walk mode constant. A full comparison of the two sets of model results is provided in Table B in Appendix B.

In these tests it was necessary to constrain both the cost and car time parameter distributions to ensure both remained negative across the range of possible values. For car time this confirms the different results with the 1986 and 2006 datasets, namely a wide distribution for 1986 and a tight distribution for 2006.

The findings from these tests that adding a distribution to the linear cost term reduces the important of log cost (1986) or results in the log-cost effect losing statistical significance altogether (2006) is consistent with the suggestion of Daly and Carrasco (2009) that the log cost term in a model without distributed parameters is capturing preference heterogeneity.

8.4 Transferability analysis

Individual parameters

To investigate the transferability of individual model parameters, the REM measure given in Equation 2.26 has been used to examine changes in parameter values between 1986 and 2006. This analysis has been made for the models with distributed parameters, and for the corresponding multinomial models without distributed parameters, with comparison of the two sets of numbers giving insight into the impact of introducing distributed model parameters on the transferability of individual model parameters. The REM measures have been averaged for the four parameter groupings used in Section 5.4.

Table 8.3: Impact of distributed parameters on parameter changes between 1986 and 2006

Parameter group	MNL spec C	Plus distrib. parameters
Cost	0.213	0.153
Car time	0.011	0.020
Other level of service	0.141	0.145
Constants	1.546	1.556
Socio economics	0.416	0.392

For cost and car time, the two parameters with distributed parameters, the REM for the mean parameter values increases when distributed parameters are introduced[1]. For the other parameters there are no substantial changes in the REM values which follows from the minor impact on these parameters of the introduction of the two distributed terms.

Statistical tests of model transferability

To assess the transferability of model specifications with and without distributed parameters, the 1986 models have been transferred to 2006 and the fit to the transfer data has been calculated. The results are presented in Table 8.4.

The fit of the model with distributed parameters to the 1986 data is significantly worse than the fit of the corresponding model without distributed parameters[2].

[1] For the cost terms, the 1986 model has a fixed log-cost term in addition to the triangularly distributed linear cost term whereas the 2006 model has just a triangularly distributed linear cost term

[2] The fit is some much worse that the result at first appeared erroneous, however tests have

Table 8.4: Mixed logit statistical tests of transferability, 1986 base

	MNL spec C	Plus distrib. parameters	Difference
$LL_{2006}(\beta_{1986})$	-391,657.8	-441,564.0	-44,525.8

As the fit is also worse than that of the reference model[3] a negative TI value results. Thus the addition of the distributed parameters has significantly reduced the transferability of the 1986 model to the 2006 data.

The same set of tests have been run for the 2006 models, which have been transferred back to 1986. The results are presented in Table 8.5.

Table 8.5: Mixed logit statistical tests of transferability, 2006 base

	MNL spec C	Plus distrib. parameters	Difference
$LL_{1986}(\beta_{2006})$	-287,146.5	-287,142.7	3.8

In contrast to the 1986 models, for the 2006 models a modest improvement in fit to the transfer context is observed when distributed parameters are added. However, this gain in fit is modest compared to the 134.0 gain in likelihood observed when distributed parameters were added to the 2006 model specification (see Table 8.2).

Predictive tests

The predictive performance of the models with and without distributed parameters has been compared. The analysis procedures set out in Section 6.3 have been repeated to examine fit to observed mode shares and tour lengths by mode. Table 8.6 summarises the results obtained when the 1986 models are used to predict mode share and tour lengths in 2006.

confirmed that the likelihood was calculated correctly.

[3] A model with constants and tour length terms by mode only.

Table 8.6: Mixed logit predictive tests, 1986 base transferred to 2006

	MNL spec C	Plus distrib. parameters
Mode share	1.7%	3.6%
Tour length (km)	1.6	4.1

The predictive performance of the model with distributed parameters is worse for both mode share and tour length by mode. This is consistent with the worse overall model fit in the transfer context highlighted in Table 8.4.

Table 8.7 presents the corresponding results for the 2006 base models transferred to 1986.

Table 8.7: Mixed logit predictive tests, 2006 base transferred to 1986

	MNL spec C	Plus distrib. parameters
Mode share	3.1%	3.1%
Tour length (km)	2.8	2.9

The predictive performance of the 2006 base model is little changed by the introduction of the two distributed parameters, consistent with the small difference in fit to the 1986 data in Table 8.5.

Elasticity tests

The procedure used to assess the impact of the introduction of the distributed parameters on the model elasticities also followed the approach set out in Section 6.4. Given the finding in Section 8.3 that the changes on the other level of service parameters (including PT in vehicle time) was small the analysis focussed on the fuel cost kilometrage and car time elasticity tests to restrict the number of model runs made.

Table 8.8 summarises the results from the elasticity analysis, with 'DB' in the table denoting distributed parameters.

Table 8.8: Mixed logit elasticity tests

Elasticity	1986		2006		1986 transfer to 2006	
	MNL	plus DB	MNL	plus DB	MNL	plus DB
Fuel cost, km	-0.157	-0.232	-0.274	-0.242	-0.188	-0.117
Car time, trip	-0.124	-0.145	-0.093	-0.095	-0.065	-0.057

For the 1986 models, the fuel cost elasticity kilometrage is lower in the model without random parameters. However, this model includes a log cost term which damps the kilometrage elasticity. A model without log cost gave an elasticity of -0.221 which is close to the value for the model with random parameters. For the 2006 models where the model specification is identical apart from the distributed terms, there is little change in the elasticities. Thus, the results suggest accounting for taste heterogeneity has not substantially altered the responsiveness of the models to changes in travel cost and time in the base year.

Comparison of the 1986 elasticities to those obtained when the 1986 models are transferred to 2006 shows that the elasticities with distributed parameters reduce over the transfer period, and show greater changes relative to the base values compared to the models without distributed parameters. Model elasticities are used to validate the sensitivity of models in the base year, and so if introducing taste heterogeneity makes the model elasticities less temporally transferable this is problematic for policy analysis, as the same policy intervention would have a different impact on different forecast years.

8.5 Summary

The tests undertaken with the Toronto data found that accounting for random taste heterogeneity led to an increase in fit to the data, which is consistent with the findings of other researchers. Introducing heterogeneity in sensitivity to linear cost reduced the role of the fixed log cost parameter. This is consistent with the findings of Daly and Carrasco (2009) who suggested that in model without random taste heterogeneity the log cost term accounts for preference heterogeneity through a self-selection effect rather than by representing variation in cost sensitivity with distance at an individual level.

Analysis of changes in individual parameter values demonstrated that the introduction of random taste heterogeneity had little impact on the other parameters. The mode constants were an exception, and in particular the walk constants changed substantially which suggests that the introduction of random taste heterogeneity had impacted on short tours in particular.

A key finding was that there was no evidence from the transferability analysis that the improvement in fit in the base context resulting in improvements in model transferability. Furthermore, for transfers from 1986 to 2006 the model with distributed parameters was noticeably worse than for the model without distributed parameters, and the introduction of taste heterogeneity had reduced the temporal transferability of the model elasticities. Further analysis to be better understand the impact on the elasticities is an area where further research would be valuable.

In Chapters 5 and 6, evidence was presented that improving the specification of models with fixed parameters to account for variation in tastes between different socio-economic groups resulted in improvements in model transferability. It is noteworthy therefore that further improving model specification does not lead to further improvements in model transferability. A possible explanation is that the random taste heterogeneity models are over-fitting the base year data, particularly for the 1986 model which transfers poorly and in which the car time parameter has a much wider spread than in the 2006 model.

Chapter 9

Conclusions and recommendations

This chapter presents the conclusions from this research, and then sets out recommendations for further work.

9.1 Mode-destination models over long-term forecasting horizons

Accounting for changes in cost sensitivity

The evidence from the literature reviewed in Daly and Fox (2012) is that the longitudinal elasticity of value of time to real income growth is around one. Tests were made using the Toronto and Sydney datasets to assess this approach relative to making no adjustment to cost sensitivity, and overall the tests concluded cost sensitivity should indeed be adjusted in this way.

A complication in models that incorporate variation in cost sensitivity with income band is that some income growth comes about due to re-distribution between income bands. The literature suggests that the cross-sectional elasticities average around 0.3, i.e. significantly lower than the longitudinal values, and using the Sydney data an approach was developed and tested to take proper account of these two effects by implementing separate cross-sectional and re-distribution income elasticities.

Model transferability

Statistical tests strongly rejected the hypothesis that the base and transfer parameters are not statistically different for all transfers tested on the Toronto and Sydney datasets. This finding is consistent with transferability tests of mode choice models reported in the literature, and indeed some studies demonstrated models to be useful at predicting behaviour in the transfer context despite the rejection of the hypothesis of parameter equality.

Therefore assessments of overall model transferability have focussed instead on the transferability index (TI), a relative measure which assessed the predictive ability of the transferred model compared to the same model specification re-estimated in the transfer context. The conclusions from the TI tests support the notion of model transferability, with the transferred commute models giving around 75% of the predictive ability of the model re-estimated in the transfer context in the Toronto tests, and at least 80% in the Sydney tests. Thus, overall the results support the notion that the models are reasonably transferable and as such suitable for use in forecasting.

Four separate years of Toronto data were available for analysis, enabling investigation of how model transferability changes over time. Interestingly, the analysis of TI values found no evidence of changes over time for transfer periods ranging from 5 to 20 years.

In all of the Toronto tests, and most of the Sydney tests, a pattern on increasing TI with improvements to model specification made using fixed parameters did emerge, a result that is consistent with the mode choice transferability literature. The conclusion for model developers is that improvements in model specification, particularly when car availability terms are added to the model specification, are justified by improved model transferability. This is a useful result, because model developers may be under pressure to keep model specifications parsimonious to make models easier to implement. For example, a model without a car availability specification avoids the need to make forecasts of how car availability changes in the future. However, it should be noted that this result did not extend to improving the model specification by adding random parameters to account for heterogeneity in cost and time sensitivity.

Tests of the predictive ability of the models, assessed by their ability to predict observed changes in overall mode share and tour length by mode, demonstrated that they were reasonably able to predict the key changes observed over the years studied. However, they did exhibit a general tendency to over-predict the observed increase in the car driver mode share, an issue which is discussed further in Section 9.5 below.

Elasticities provide an important measure of overall model sensitivity for model developers, as they are a dimensionless measure that can be compared between models and in a UK context there are expectations for the range of acceptable elasticity values. Further, they capture the sensitivity of the models to changes in travel cost and travel time which are the key changes resulting from many policy measures.

The elasticity analysis suggested that the model elasticities are reasonably transferable between base and transfer contexts. An important point the analysis highlighted was that the elasticity values associated with a particular model are significantly impacted by the parameter estimates for that model, and in particular in these models the balance of linear and log cost effects. This impacts upon analysis of the how the elasticities change over time, making it difficult to separate out any true behavioural change in sensitivity over time.

Parameter transferability

For both the Toronto and Sydney transferability analyses, models were estimated by pooling over each available year of data and estimating model scales by year. These scale parameters were then used to take account of variation in model scale (i.e. levels of unexplained error) when comparing models estimated separately from different years of data. This is the correct approach when comparing models estimated from different years of data, but it is one that is frequently overlooked in the temporal transferability literature.

Analysis was undertaken to investigate the transferability of different groups of model parameters, namely cost terms, level of service terms, socio-economic terms and constants. This analysis found the level of service terms to be the most transferable, the cost and socio-economic parameters to be somewhat less transferable, and the constants to be by some way the least transferable group. The finding that the constants are the least transferable group is not unexpected, as they represent the mean effect of unmeasured effects not captured in the other terms and no insight into how these unmeasured effects might change in the future.

The high level of stability observed in the in-vehicle time parameter values provides evidence that the approach to adjusting the models to take account of VOT growth over time, which is applied through adjustments to the cost sensitivity terms alone on the assumption that travel time sensitivity is temporally stable, is reasonable.

Many transport policy measures can be formulated in terms of changes in travel cost and/or travel times. The result that level-of-service terms, which includes sensitivity to travel times, are more transferable than the cost terms is therefore important. It might be expected that this result would have played out in the elasticity analysis, i.e. the travel time elasticities would have been observed to be more transferable than the cost elasticities, but this result was not observed. As discussed in Section 9.6, this is an area where further analysis would be valuable.

The relative sensitivities of mode and destination choice were estimated in the models, and therefore the model results allow investigation of how these relative sensitivities change over time. For the Toronto commute analysis, a destinations-above-modes structure was found to give the best fit to the data, and the structural parameters were remarkably stable over time. For the Sydney commute and home–other travel analyses, modes-above-destinations structures gave the best fit to the 1991 data, but the difference between the mode and destination sensitivities reduced between 1991 and 2006 so that the 2006 structures were closer to a multinomial structure where both choices are equally sensitive to changes in utility. However, this result is believed to be impacted by the significant change in zone system between 1991 and 2006 which results in changes in the destination choice error (sensitivity).

Comparison of Toronto and Sydney results

Commute models were developed using both the Toronto and Sydney datasets, allowing comparison of the two sets of transferability analysis.

For the best specification, models for both datasets had good transferability overall. The Sydney models had higher transferability, consistent with the richer socio-economic segmentation in the models and the more detailed treatment of public transport modes.

Both sets of results supported the finding that improving model specification improves model transferability, with the largest improvements coming about when car availability parameters were added to the specifications.

The predictive tests demonstrated that the two sets of transferred models performed similarly when predicting the observed changes in mode share and tour length over the transfer period. In both cases, the growth in the car driver share was over-predicted. No significant differences between the two sets of models emerged from the elasticity analysis either.

It is noteworthy that while the Toronto results suggest the mode destination structures to be temporally stable within a given study area, comparison of the Toronto and Sydney commute model structures suggests they they are not spatially transferable.

Overall, the Toronto and Sydney commute transferability analyses gave rise to consistent findings.

9.2 Commuter and non-commuter travel

Comparison of commuter and non-commuter travel

It was not possible to obtain the Toronto home–other[1] tour samples for this analysis. However, the Sydney data was available for all purposes and therefore was used to make analysis to compare the transferability of commute and home–other travel.

Model transferability was assessed using the TI measure for different model specifications. This analysis demonstrated the home–other work models to be consistently less transferable than the equivalent commute models. However, as

[1]All travel that is not for commute, business, education or shopping purposes. This includes serve passenger, personal business and leisure travel.

per the commute models the transferability of the home–other travel models improves when the model specification improves, particular when car availability parameters are added to the model specification.

The predictive ability of the transferred home–other travel models, assessed by their ability to forecast observed changes in mode share and tour length, was similar to that of the commute models.

The elasticities of the transferred models were consistently lower than the elasticity for the same model specification re-estimated on the transfer data, however it is believed that the change in zone system between 1991 and 2006 and the associated changes in level of service play a significant role in this result.

Analysis of changes in the individual parameters by parameter group showed that the home–other travel parameters were consistently less transferable than the commute values, with the transferability of the level of service parameters noticeably worse than in the commute model. Again, a possible contribution to this result is the significant changes in the zoning and level of service between 1991 and 2006 which impacted more significantly on the home–other results because the tour lengths are shorter.

Overall it is concluded that the home–other travel models are less transferable than those for commute. Therefore researchers need to be cautious about making conclusions about model transferability based on commute travel alone, as the review of the temporal transferability literature presented in Section 2.4 demonstrated that most previous work has done.

Home–other travel sub-purpose tests

A plausible hypothesis for the lower transferability of home–other travel models is that the purpose covers a heterogenous range of sub-purposes. Therefore tests were made whereby separate models were developed for three sub-purposes –

serve passenger, personal business and leisure – and then the transferability of these models compared to that observed for modelling these three sub-purposes together.

In terms of overall fit to the transfer data, the separate sub-purpose models gave a better fit compared to modelling the three purposes together as a single purpose for both possible transfers, i.e. from 1991 to 2006 and from 2006 back to 1991. However, tests of the ability of the sub-purpose models to predict the observed changes in mode share and tour length showed no improvement relative to modelling the three sub-purposes together in a single model.

Analysis of model elasticities provided some evidence of variation in the fuel cost kilometrage elasticity between sub purposes. However, the impact of the significant changes in zoning system prevented conclusions being drawn about the transferability of elasticity values in the sub-purpose models.

Analysis of changes in individual parameters by parameter group showed that overall the sub-purpose model parameters were more transferable than those obtained when the three sub-purposes were modelled together. Particularly noticeable improvements in transferability were obtained for the model constants, a plausible result given that mode and destination choice patterns would be expected to vary between the three sub-purposes.

Overall, on the basis of fit to the transfer data and the analysis of changes in individual parameters it is concluded that segmenting home–other travel into separate sub-purposes does result in more transferable models. However, taken together these sub-purposes models are still less transferable than the comparable commute models.

9.3 Evolution of model scale and constants

If data is available in the base and transfer contexts, then a model can be estimated by pooling the data and estimating a scale capturing the different levels of error in the base and transfer contexts. This is the approach that has been used in this analysis to account for scale differences when comparing models estimated from different years, but it is approach that is not always followed by other researchers.

The analysis of the evolution of model scales over time presented in Chapter 7 did not identify any patterns whereby particular parameters groups increased or reduced in scale over time. While this is consistent with the unexpected finding that model transferability did not reduce over time, it does mean that the analysis of changes in scale by parameter group over time was less insightful than had been hoped.

One of the scale parameters that was estimated was for the mode and destination constants, and therefore no clear insights emerged from this particular analysis on changes in the constants over time. However, the analysis of changes in the individual parameters between years clearly demonstrated the constants to be less temporally transferable than other parameter groups.

9.4 Accounting for random taste heterogeneity

Accounting for random heterogeneity in sensitivity to cost and car time was found to give significant improvements in fit to the base data. Introducing heterogeneity in sensitivity to linear cost reduced or eliminated the role of the log cost term identified in models without taste heterogeneity. This is consistent with the findings of Daly and Carrasco (2009), who suggested that the log cost term accounts for taste heterogeneity through a self-selection effect rather than representing variation in value of time with distance at an individual level. Analysis of changes in individual parameters demonstrated that the introduction of parameter distributions had little impact on the fixed parameters.

The key finding was that there was no evidence that the improvement in fit in the base context resulted in more transferable models, in fact for one of the transfers the model with distributed parameters was noticeably worse than the model without distributed parameters which may be explained by the model over-fitting the base year data. Table 9.1 summarises the results from the random taste heterogeneity tests.

Table 9.1: Random taste heterogeneity tests

Context	Impact on model results
Base	Significant improvement in fit, however this may be due to over-fitting
Transfer	No improvement in fit relative to models without random terms

The wider implication for researchers is that they cannot assume that improvements in fit to the base year data resulting from accounting for taste heterogeneity will result in better quality forecasts. In most practical cases, it is not possible to validate models using data collected at different points in time. Therefore, a sensible approach would be to retain a holdout sample in the base year, and test whether model specifications that account for taste heterogeneity are better able to explain the choices observed in the holdout sample.

9.5 Guidance on maximising model transferability

The Sydney analysis demonstrated that substantial changes in the level of service following the move to a more detailed zoning system had a significant impact on the models, and in particular the model sensitivities. Thus a clear recommendation is that models should be applied using level of service that is generated on a consistent basis to the data used in model estimation.

Drawing on literature and the empirical analysis presented in this thesis, it is recommended that in forecasting the cost sensitivity terms are adjusted to take account of the impact of real income growth on values of time using a longitudinal elasticity of 1. The in-vehicle time parameters have been shown to have a good level of temporal stability, and thus applying the the value-of-time adjustment by adjusting the cost parameter while holding the time parameter constant appears to be reasonable.

When applying models that incorporate variation in cost sensitivity with income band, account should be taken of the impact of the cross-sectional income elasticity which will result in an overall value of time growth because of shifts from lower to higher income bands over time[2] The cross-sectional elasticities are typically lower than the longitudinal values, with evidence in the literature and results from the Sydney analysis suggesting average values of around -0.3.

A clear finding from the empirical analysis that is consistent with the mode choice transferability literature is that improving model specification using fixed parameters to account for variation in preference between socio-economic groups improves model transferability. Particularly noticeable improvements were observed when car availability terms were added to the model specifications. This is an important result for model developers who may be under pressure to keep model specifications as parsimonious as possible to simplify model implementation. However, as discussed in Section 9.4 there was no evidence from the tests undertaken that accounting for heterogeneity in cost and travel time sensitivity results in improved model transferability, and indeed models of this type may over-fit the base data resulting in worse transferability compared to models with

[2] Assuming incomes rise over the forecast period.

fixed parameters.

If data from multiple years is available for model development, then pooling over different years can give more transferable models than using the most recent data alone. This approach may be particularly valuable if a smaller more recent survey is available alongside a larger older survey. If data is combined in this way, then the older data should be scaled relative to the more recent data to account for changes in scale over time, and separate mode constants should be estimated by year, with the most recent mode constants retained for forecasting.

9.6 Recommendations for further work

Assessments of the ability of the Toronto and Sydney models to predict observed changes in mode share and tour length highlighted a consistent pattern of over-prediction of the increase in the car driver share over time. In both cases this increase has been accompanied by a significant real terms increase in car costs, and so a potential explanation is that the models which are estimated from cross-sectional data are under-sensitive to the longitudinal change in costs. However, at the same time as the increase in car costs, congestion and associated parking difficulties have increased. Further analysis would be valuable to explore these different factors and better investigate whether there are differences between the cross-sectional and longitudinal cost sensitivities.

A conclusion from the analysis of changes in model elasticity (sensitivity) is that further research would be valuable to try to better disentangle changes in model sensitivity – which are impacted by differences in the relative strength of particular model parameters between different years – from the evolution of changes in the underlying sensitivity of travellers to cost and time changes. Related to this, there is a wider lack of evidence on how elasticities are evolving over time.

The finding that models which incorporated preference heterogeneity were no more, and potentially much less, transferable than models without results in a clear recommendation that other researchers should consider what evidence exists to demonstrate that improvements in fit to the base year data yields models that are better able to forecast behaviour. As discussed above, using holdout samples to test whether models incorporating taste heterogeneity give better base year predictions is one possible approach when a transfer sample is not available. Further work would also be valuable to explore whether the assumptions around the shape of parameter distribution have an impact on model transferability, for example by investigating whether different distributions give the best fit for different years of data.

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Appendix A

Temporal stability analysis

To test whether individual parameters were stable over time, Equation 2.25 was used to test the null hypothesis that the base and transfer parameters were equal, but only when both base and transfer parameters were significant at a 95% level[1]. To provide an assessment of the magnitude of the differences between parameters, the REM statistic defined in Equation 2.27 was used. The detailed results are presented in Appendix A, but Table A.1 summarises the key results by the three groups of parameters.

In Table A.1, the 'Acc' columns give the number of model parameters where the hypothesis that the parameters are stable is accepted at a 95% confidence level, the 'Rej' columns give the number of model parameters where the hypothesis of stability was rejected at a 95% confidence level, and the 'Insig' columns give the number of cases where the comparison could not be made because the base and/or transfer parameter was not significant. The 'REM' columns present the mean REM statistic for the parameters in that group. The Sanko results were

[1] Otherwise the null hypothesis may be accepted even if the base and transfer parameters are substantially different.

excluded from this analysis on the basis that that omission of cost and car availability information from his models resulted in significant bias to the other terms, particularly the mode constants.

The full set of parameter values for each of the studies is presented below.

Table A.1: Tests of temporal parameter stability

		Cost terms				LOS terms				Socio-economic terms				Mode constants			
Study	Period	Acc	Rej	Insig	REM	Acc	Rej	Insig	REM	Acc	Rej	Insig	REM	Acc	Rej	Insig	REM
Train	3 years	1	0	0	0.06	4	0	2	0.20	8	0	4	1.12	3	0	0	0.36
Silman	4 years	0	0	1	0.24	2	0	2	0.11	2	2	1	0.44	2	0	0	0.33
Kozel	6 years	0	0	1	2.06	0	0	1	1.09	4	2	3	0.67	0	0	2	0.90
Badoe	22 years	1	1	0	0.18	1	4	0	0.46	no terms				0	0	2	2.05
Forsey	5 years	1	0	0	0.03	1	5	0	1.11	4	17	2	0.92	0	6	0	0.10
Karas.	7 years	0	1	0	1.80	1	2	0	0.92	1	0	0	0.09	1	0	1	2.85
Gunn	13 years	1	0	0	0.03	3	1	1	0.24	1	0	1	0.13	not reported			
Overall		50%	25%	25%	0.71	39%	42%	19%	0.59	38%	40%	21%	0.56	35%	35%	29%	1.10

Table A.2: Temporal stability analysis, Train(1978)

	β_{72} (t-ratio)	β_{75} (t-ratio)	β_{75}/β_{72}	$\lvert\beta_{75}-\beta_{72}\rvert$	$\beta_{75}=\beta_{72}$?	REM
Cost/wage rate	-0.0284 (4.31)	-0.0266 (3.92)	0.94	0.00 (0.2)	yes	0.063
Car time	-0.0644 (5.65)	-0.0473 (3.48)	0.73	0.02 (1.0)	yes	0.266
PT IVT	-0.0259 (5.65)	-0.0197 (2.03)	0.76	0.01 (0.6)	yes	0.239
Walk time	-0.0689 (5.28)	-0.0900 (3.36)	1.31	0.02 (0.7)	yes	0.306
Transfer wait time	-0.0538 (2.30)	-0.0438 (1.81)	0.81	0.01 (0.3)	insignif.	0.186
Transfers	-0.105 (0.78)	-0.12 (0.86)	1.14	0.02 (0.1)	insignif.	0.143
Headway	-0.0318 (3.18)	-0.029 (2.6)	0.91	0.00 (0.2)	yes	0.088
Car, income up to 7.5 $k/yr	4.54e-5 (0.05)	2.89e-4 (1.78)	6.37	0.00 (0.4)	insignif.	7.366
Car, income 7.5-10.5 $k/yr	-5.72e-5 (0.43)	5.22e-5 (0.364)	-0.91	0.00 (0.6)	insignif.	1.913
Car, income 10.5-15.5 $k/yr	5.43e-5 (0.91)	-4.19e-5 (0.74)	0.77	0.00 (0.2)	insignif.	0.228
Car, no. drivers	1.02 (4.81)	1.48 (5.26)	1.45	0.46 (1.3)	yes	0.451
Bus, car acc., no. drivers	0.99 (3.29)	1.65 (5.16)	1.67	0.66 (1.5)	yes	0.667
Carpool, no. drivers	0.872 (4.25)	1.28 (4.85)	1.47	0.41 (1.2)	yes	0.468
Car, head of hh	0.627 (3.37)	0.668 (3.19)	1.07	0.04 (0.1)	yes	0.065
Car. employment density	-0.0016 (2.27)	-0.0016 (3.45)	1.03	0.00 (0.0)	yes	0.025
Car, home in or near CBD	-0.502 (4.18)	0.1546 (0.84)	-0.31	0.66 (3.0)	insignif.	1.308
Car, cars per driver	5.00 (9.65)	4.79 (3.70)	0.96	0.21 (0.2)	yes	0.042
Bus, car acc., cars per driver	2.33 (2.74)	3.63 (4.81)	1.56	1.30 (1.1)	yes	0.558
Carpool, cars per driver	2.38 (5.28)	3.26 (3.19)	1.37	0.88 (0.8)	yes	0.383
Car (alone)	-5.26 (5.93)	-4.18 (2.82)	0.79	1.08 (0.6)	yes	0.205
Bus, car access	-5.49 (5.33)	-8.24 (6.67)	1.50	2.75 (1.7)	yes	0.501
Car pool	-3.84 (3.84)	-5.31 (5.56)	1.38	1.47 (1.1)	yes	0.383

Table A.3: Temporal stability analysis, Silman(1981)

	β_{72} (t-ratio)	β_{76} (t-ratio)	β_{76}/β_{72}	$\lvert\beta_{76}-\beta_{72}\rvert$	$\beta_{76}=\beta_{72}$?	REM
Cost (generic)	-0.0010 (0.4)	-0.0008 (0.5)	0.76	0.00 (0.1)	insignif.	0.243
IVT (generic)	-0.033 (1.6)	-0.030 (1.8)	0.90	0.00 (0.1)	insignif.	0.105
CD park time	-0.302 (2.4)	-0.257 (2.4)	0.85	0.05 (0.3)	yes	0.149
CP park time	-0.069 (0.6)	-0.06778 (0.5)	0.98	0.00 (0.0)	insignif.	0.023
Bus OVT/distance	-15.0 (3.0)	-12.68 (2.8)	0.85	2.32 (0.3)	yes	0.155
No of cars, CD	2.62 (6.6)	4.53 (7.6)	1.73	1.91 (2.7)	no	0.729
No of cars, CP	1.68 (7.5)	2.43 (9.5)	1.45	0.75 (2.2)	no	0.446
Years of study, CD	0.0919 (2.3)	0.0642 (2.1)	0.70	0.03 (0.6)	yes	0.301
Years of study, CP	0.0584 (1.6)	0.0221 (6.5)	0.38	0.04 (1.0)	insignif.	0.622
HOH dummy	3.37 (15.0)	3.01 (6.5)	0.89	0.36 (0.7)	yes	0.107
CD constant	-5.00 (6.8)	-6.83 (9.0)	1.37	1.83 (1.7)	yes	0.366
CP constant	-3.37 (6.6)	-4.36 (9.7)	1.29	0.99 (1.5)	yes	0.294

Table A.4: Temporal stability analysis, Kozel(1981)

	β_{72} (t-ratio)	β_{78} (t-ratio)	β_{78}/β_{72}	$\lvert\beta_{78}-\beta_{72}\rvert$	$\beta_{78}=\beta_{72}$?	REM
Cost/wage rate	-0.301 (1)	-1.083 (4)	3.60	0.78 (1.9)	insignif	2.598
Motorised IVT	-0.026 (1.3)	-0.0675 (2.5)	2.60	0.04 (1.2)	insignif	1.596
Walk time	-0.0688 (6)	-0.1083 (9.4)	1.57	0.04 (2.4)	no	0.574
Income, car drive/pass.	0.00013 (3.2)	0.00017 (6.6)	1.31	0.00004 (0.8)	yes	0.308
Income, taxi	0.00018 (4.2)	0.00018 (5.8)	1.00	0.00000 (0.0)	yes	0.000
Income, buseta/microbus	0.0001 (2.7)	0.00011 (6.1)	1.10	0 (0.2)	yes	0.100
Income, walk	-0.00003 (0.4)	-0.00002 (0.6)	0.67	0 (0.1)	insignif	0.333
Head household, car drive/pass.	1.616 (5.2)	2.192 (7.8)	1.36	0.58 (1.4)	yes	0.356
Head household, walk	0.263 (0.6)	0.672 (2.5)	2.56	0.41 (0.8)	insignif	1.555
Car comp., car drive/pass.	3.45 (4.0)	1.107 (2.2)	0.32	2.34 (2.3)	no	0.679
Car comp., buseta	2.333 (3.4)	-0.117 (0.3)	-0.05	2.45 (3.1)	insignif	1.050
Car comp., walk	2.702 (2.4)	-1.707 (2.1)	-0.63	4.41 (3.2)	no	1.632
Drive/passenger	-1.696 (3.0)	-2.41 (4.5)	1.42	0.71 (0.9)	yes	0.421
Taxi/collective taxi	-2.167 (5.7)	-3.749 (6.9)	1.73	1.58 (2.4)	no	0.730
Buseta	-1.302 (6.2)	-0.761 (6.2)	0.58	0.54 (2.2)	no	0.416
Walk	0.754 (0.9)	2.287 (4.9)	3.03	1.53 (1.6)	insignif	2.033

Table A.5: Temporal stability analysis, Badoe and Miller (1995)

	β_{64} (t-ratio)	β_{86} (t-ratio)	β_{86}/β_{64}	$\lvert\beta_{86} - \beta_{64}\rvert$	$\beta_{86} = \beta_{64}$?	REM
Cost	-0.364 (-4.7)	-0.381 (-4.7)	1.05	0.02 (0.2)	yes	0.047
Parking cost	-0.335 (-14.7)	-0.229 (-31.6)	0.68	0.11 (4.4)	no	0.316
Car time	-0.031 (-13.5)	-0.053 (-12.3)	1.71	0.02 (4.5)	no	0.710
PT IVT	-0.042 (-11.9)	-0.040 (-15.9)	0.95	0.00 (0.5)	yes	0.048
PT wait time	-0.206 (-15.8)	-0.117 (-12.8)	0.57	0.09 (5.6)	no	0.432
PT walk time	-0.046 (-4.0)	-0.084 (-13.5)	1.83	0.04 (2.9)	no	0.826
Walk distance	-1.933 (-27.6)	-1.408 (-32.3)	0.73	0.53 (6.4)	no	0.272
CD constant	0.108 (0.7)	0.452 (6.3)	4.19	0.34 (2.0)	insignif.	3.185
Walk constant	0.898 (4.8)	0.069 (0.7)	0.08	0.83 (3.8)	insignif.	0.923

Table A.6: Temporal stability analysis, Forsey (2012)

	β_{01} (t-ratio)	β_{06} (t-ratio)	β_{06}/β_{01}	$\lvert\beta_{06}-\beta_{01}\rvert$	$\beta_{06}=\beta_{01}$?	REM
Cost	-0.154 (-38.8)	-0.150 (-33.2)	0.97	0.00 (0.7)	yes	0.026
IVT	-0.014 (-21.1)	-0.021 (-27.3)	1.45	0.01 (6.3)	no	0.451
Walk time	-0.007 (-4.8)	-0.044 (-27.6)	6.40	0.04 (17.3)	no	5.397
Wait time	-0.070 (-27.2)	-0.090 (-32.2)	1.30	0.02 (5.4)	no	0.296
NM dist u1	6.225 (76.0)	7.862 (75.2)	1.26	1.64 (12.3)	no	0.263
NM dist 1 to 2	4.897 (66.4)	5.767 (64.8)	1.18	0.87 (7.5)	no	0.178
NM dist 2 to 3	3.383 (42.8)	3.591 (37.5)	1.06	0.21 (1.7)	yes	0.062
1 veh CP	1.263 (32.9)	1.580 (31.6)	1.25	0.32 (5.0)	no	0.251
2+ veh CP	1.892 (44.6)	2.280 (40.2)	1.20	0.39 (5.5)	no	0.205
2 veh CD	1.529 (70.0)	1.843 (72.1)	1.20	0.31 (9.3)	no	0.205
3+ veh CD	1.927 (77.9)	2.277 (80.7)	1.18	0.35 (9.3)	no	0.182
nveh SAA	1.162 (37.9)	1.317 (36.2)	1.13	0.16 (3.3)	no	0.134
nveh GRA	4.609 (104.4)	4.672 (94.5)	1.01	0.06 (1.0)	yes	0.014
male CP	-0.874 (68.0)	-0.819 (-67.4)	0.94	0.05 (3.1)	no	0.062
male LT	-0.827 (-36.9)	-0.606 (-24.5)	0.73	0.22 (6.6)	no	0.267
male SA	-0.480 (-10.1)	-0.355 (-6.7)	0.74	0.13 (1.8)	yes	0.261
male GRA	1.163 (15.2)	1.799 (22.4)	1.55	0.64 (5.7)	no	0.546
male NM	-0.497 (-12.4)	-0.408 (-8.9)	0.82	0.09 (1.5)	yes	0.178
up to 25 CP	1.186 (66.1)	1.473 (77.0)	1.24	0.29 (10.9)	no	0.242
up to 25 LT, GRT	1.104 (36.4)	1.388 (38.0)	1.26	0.28 (6.0)	no	0.258
up to 25 NM	1.378 (26.8)	1.602 (24.0)	1.16	0.22 (2.7)	no	0.163
25-30 CP	0.259 (13.5)	0.196 (9.6)	0.75	0.06 (2.3)	no	0.246
25-30 LT, GRT	0.497 (16.1)	0.517 (13.6)	1.04	0.02 (0.4)	yes	0.041
25-30 SA, GRA	0.428 (6.6)	-0.495 (6.6)	-1.16	0.92 (9.3)	no	2.156
25-30 NM	0.502 (7.1)	-0.167 (-1.8)	-0.33	0.67 (5.8)	insignif.	1.333
55+ SA, GRA	0.040 (0.5)	-0.375 (4.7)	-9.30	0.42 (3.6)	insignif.	10.303
55+ NM	-0.133 (2.0)	0.176 (2.8)	-1.33	0.31 (3.3)	no	2.330
Metropass, LT, SA	2.510 (63.8)	3.266 (75.3)	1.30	0.76 (12.9)	no	0.301
Other pass, LT, SA	1.808 (17.7)	4.021 (58.9)	2.22	2.21 (18.0)	no	1.224
GO pass, GRA, GRT	2.030 (27.9)	2.512 (33.7)	1.24	0.48 (4.6)	no	0.237
CD constant	7.990 (121.9)	8.461 (108.4)	1.06	0.47 (4.6)	no	0.059
CP constant	5.418 (83.1)	5.808 (74.8)	1.07	0.39 (3.8)	no	0.072
LT constant	7.217 (96.1)	8.382 (93.8)	1.16	1.16 (10.0)	no	0.161
SA constant	6.986 (77.1)	7.736 (74.2)	1.11	0.75 (5.4)	no	0.107
GRA constant	8.750 (103.1)	9.464 (91.6)	1.08	0.71 (5.3)	no	0.082
NM constant	2.215 (26.9)	1.921 (21.3)	0.87	0.29 (2.4)	no	0.133

Table A.7: temporal stability analysis, Sanko (2013)

	β_{1971} (t-ratio)	β_{2001} (t-ratio)	$\beta_{2001}/\beta_{1971}$	$\lvert\beta_{2001}-\beta_{1971}\rvert$	$\beta_{2001}=\beta_{1971}$?	REM
Travel time	-0.606 (6.9)	-2.60 (20.5)	4.29	1.99 (12.9)	no	3.29
Male, rail	0.577 (8.6)	0.511 (3.9)	0.89	0.07 (0.4)	yes	0.11
Male, car	1.970 (29.4)	1.38 (10.9)	0.70	0.59 (4.1)	no	0.30
Aged 20+, car	0.900 (8.3)	0.511 (2.1)	0.57	0.39 (1.9)	yes	0.43
Aged 65+, bus	1.910 (8.9)	0.561 (2.1)	0.29	1.35 (3.9)	no	0.71
Nagoya, car	-1.120 (24.1)	-2.210 (36.7)	1.97	1.09 (14.3)	yes	0.97
Bus constant	-0.127 (2.4)	-1.03 (12.1)	-8.11	1.16 (11.6)	no	9.11
Car constant	-1.150 (9.8)	-0.560 (2.2)	-0.49	1.71 (6.2)	yes	1.49

Table A.8: Temporal stability analysis, Karasmaa and Pursula (1997)

	β_{81} (t-ratio)	β_{88} (t-ratio)	β_{88}/β_{81}	$\lvert\beta_{88} - \beta_{81}\rvert$	$\beta_{88} = \beta_{81}$?	REM
Cost/income (PT, car)	-0.704 (-13.9)	-1.97 (26.6)	2.80	1.27 (14.2)	no	1.80
Travel time (PT, car)	-0.0207 (9.0)	-0.0199 (8.3)	0.96	0.00 (0.2)	yes	0.04
Transfers (PT)	-0.138 (3.0)	-0.376 (10.1)	2.71	0.24 (4.0)	no	1.71
Ln(distance) (walk)	-2.96 (21.1)	-3.38 (29.7)	1.14	0.42 (2.3)	no	0.14
Cars/hhld (car)	0.528 (2.6)	0.574 (5.5)	1.09	0.05 (0.2)	yes	0.09
CD constant	0.157 (0.6)	-0.713 (-4.8)	-4.54	0.87 (3.0)	no	5.54
Walk constant	1.34 (9.1)	1.13 (9.9)	0.84	0.22 (1.2)	yes	0.16

Table A.9: temporal stability analysis, Gunn (2001)

	β_{82} (t-ratio)	β_{95} (t-ratio)	β_{95}/β_{82}	$\lvert\beta_{95}-\beta_{82}\rvert$	$\beta_{95}=\beta_{82}$?	REM
Log cost	-0.782 (5.3)	-0.757 (32.5)	0.97	0.03 (0.2)	yes	0.03
Car time	-0.053 (5.7)	-0.054 (52.6)	1.02	0.00 (0.1)	yes	0.02
PT IVT	-0.044 (17.9)	-0.019 (43.4)	0.43	0.03 (10.0)	no	0.57
PT walk time	-0.036 (4.7)	-0.035 (18.7)	0.97	0.00 (0.1)	yes	0.03
PT headway	-0.027 (1.9)	-0.019 (19.7)	0.70	0.01 (0.6)	yes	0.30
Slow dist	-0.278 (6.2)	-0.197 (35.5)	0.71	0.08 (1.8)	yes	0.29
Car comp, driver	3.56 (9.4)	2.85 (54.0)	0.80	0.71 (1.8)	yes	0.20
Car comp, pass.	0.843 (1.6)	0.895 (12.8)	1.06	0.05 (0.1)	yes	0.06

Appendix B

Toronto model results

The following tables present the model parameter values. In the tables, in each column the parameter value β is presented on the left and the t-ratio for the parameter is presented on the right. The t-ratio is given by the ratio β/σ where σ is the standard deviation of the parameter estimate. For model parameters, the t-ratios define the significance of the parameter relative to a value of zero. For the structural parameters and the scale parameters the t-ratios have been presented relative to a value of one. The estimation outputs give the significance of all parameters relative to a value of zero (t_0), so for the structural and scale parameters these have been converted into values relative to one (t_1) using the following expression:

$$t_1 = t_0 * \frac{|1-\beta|}{\beta} \tag{B.1}$$

In Table B.1 to Table 4.4, the cost parameters are all presented in 1986 values and prices. For the 1996, 2001 and 2006 models this means that the cost parameters have been adjusted to take account of real income growth using the procedure documented in Section 5.1.1.

In Table B.3 and Table B.4, the cost parameters are all presented in 1996 values but 1986 prices. This means that the cost parameters presented for the 1996-only models have been rescaled related to those presented in Table B.2.

The 1996, 2001 and 2006 parameters values are presented after rescaling to take account of differences in model scale between years, following the procedure described in Section 5.2.

Table B.1: Sparse model specification

	HW_MD_1986_A		HW_MD_1996_A_DX		HW_MD_2001_A		HW_MD_2006_A	
Log-likelihood		-308,802.4		-368,565.1		-478,031.4		-414,656.3
Observations		50,254		60,241		75,753		64,959
LL per obs		-6.145		-6.118		-6.310		-6.383
Cost parameters								
LogCost	-0.347	-23.1	-0.570	-32.6	0.023	1.2	-0.318	-16.1
Cost	-0.0011	-12.8	-0.0006	-8.4	-0.003	-28.2	-0.0015	-20.8
Level of service								
CarTime	-0.039	-43.9	-0.035	-43.4	-0.030	-47.2	-0.040	-38.3
TranIVT	-0.027	-41.4	-0.027	-38.8	-0.019	-36.0	-0.023	-35.5
TranWait	-0.065	-25.8	-0.058	-34.4	-0.079	-37.5	-0.062	-31.4
TranWalk	-0.031	-19.3	-0.030	-12.2	-0.023	-26.1	-0.030	-20.8
APDist	-0.022	-27.5	-0.025	-33.1	-0.022	-36.7	-0.030	-35.0
WalkDist	-0.619	-44.5	-0.717	-47.8	-0.447	-37.6	-0.634	-52.3
Destination terms								
CBDDest	0.484	14.8	0.626	17.9	-0.243	-10.0	-0.147	-5.2
CBDLT	0.138	3.6	0.153	3.5	1.067	33.0	0.960	22.8
Mode constants								
AP	-3.722	-56.7	-4.975	-65.5	-2.423	-28.0	-3.579	-47.7
LT	0.238	5.5	0.598	9.4	-0.089	-2.3	0.227	4.7
Wk	-0.650	-7.6	-1.089	-11.6	-0.447	-37.6	-0.013	-0.1
Structural parameter								
TR_D_M	0.862	59.9	0.858	59.8	0.907	53.6	0.865	52.2
Attraction term								
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a

Table B.2: Car avail model specification

	HW_MD_1986_B		HW_MD_1996_B_DX		HW_MD_2001_B		HW_MD_2006_B	
Log-likelihood		-307,487.2		-366,987.3		-475,783.4		-412,905.8
Observations		50,254		60,241		75,753		64,959
LL per obs		-6.119		-6.092		-6.281		-6.356
Cost parameters								
LogCost	-0.352	-22.7	-0.590	-33.0	0.011	0.4	-0.336	-16.2
Cost	-0.0011	-12.5	-0.0006	-7.5	-0.003	-28.2	-0.0016	-20.2
Level of service								
CarTime	-0.042	-43.6	-0.039	-42.5	-0.038	-47.1	-0.045	-42.5
TranIVT	-0.028	-40.9	-0.029	-38.8	-0.024	-37.4	-0.026	-38.8
TranWait	-0.058	-22.4	-0.050	-29.0	-0.072	-30.8	-0.051	-29.0
TranWalk	-0.027	-16.1	-0.028	-11.2	-0.023	-22.5	-0.026	-11.2
APDist	-0.022	-27.5	-0.026	-33.5	-0.026	-38.7	-0.031	-33.5
WalkDist	-0.622	-44.2	-0.710	-47.0	-0.460	-36.6	-0.627	-47.0
Destination terms								
CBDDest	0.519	15.3	0.662	18.3	-0.214	-7.4	-0.125	18.3
CBDLT	0.134	3.4	0.163	3.7	1.165	32.4	1.003	3.7
Mode constants								
AP	-4.727	-48.8	-6.052	-57.0	-3.611	-30.3	-4.497	-57.0
LT	0.581	12.6	1.050	15.8	0.430	9.5	0.689	15.8
Wk	-0.167	-1.9	-0.578	-5.9	-0.460	-36.6	0.548	-5.9
Structural parameter								
TR_D_M	0.814	58.4	0.773	57.8	0.761	53.5	0.768	57.8
Attraction term								
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a
Car availability								
AD2pVeh	1.212	39.6	1.541	40.3	1.573	50.8	1.560	40.3
AP1Veh	1.584	21.9	1.843	25.5	1.785	27.8	1.712	25.5
AP2pVeh	2.028	27.2	2.329	30.2	2.309	34.4	2.207	30.2

Table B.3: Pooled 1986 & 1996 models

	1996 model		Pooled 1		Pooled 2		Pooled 3		Pooled 4		Pooled 5	
Log-likelihood		-366,987.3		-493,983.6		-493,557.9		-491,020.8		-491,040.7		-491,008.6
gain w.r.t. Pooled 1		n/a				425.8		2962.9		2942.9		2975.0
Observations		60,241		80,373		80,373		80,373		80,373		80,373
LL per obs		-6.092		-6.146		-6.141		-6.109		-6.110		-6.109
Cost parameters												
LogCost	-0.493	-33.0	-0.247	-31.5	-0.206	-29.1	-0.353	-31.5	-0.364	-28.1	-0.381	-26.2
Cost	-0.0005	-7.5	-0.0008	-19.7	-0.0007	-19.4	-0.0007	-13.1	-0.0007	-12.7	-0.0008	-12.7
Level of service												
CarTime	-0.034	-42.5	-0.019	-57.9	-0.018	-58.0	-0.034	-51.6	-0.034	-50.5	-0.034	-49.0
TranIVT	-0.025	-38.8	0.000	0.7	-0.002	-6.0	-0.024	-47.9	-0.024	-46.8	-0.024	-44.9
TranWait	-0.043	-29.0	-0.091	-55.9	-0.082	-54.7	-0.046	-31.0	-0.045	-30.7	-0.045	-30.8
TranWalk	-0.025	-11.2	-0.038	-30.1	-0.031	-28.0	-0.023	-17.9	-0.024	-19.0	-0.023	-18.0
APDist	-0.022	-33.5	-0.019	-35.5	-0.017	-35.3	-0.020	-35.8	-0.020	-35.5	-0.020	-34.7
WalkDist	-0.615	-47.0	-0.496	-53.1	-0.446	-52.5	-0.554	-53.5	-0.539	-51.8	-0.538	-50.3
Destination terms												
CBDDest	0.573	18.3	0.303	16.9	0.265	16.5	0.475	19.7	0.515	19.4	0.554	16.3
CBDLT	0.141	3.7	0.029	1.1	0.024	1.0	0.116	4.1	0.140	4.5	0.144	4.3
Mode constants												
AP	-5.240	-57.0	-3.909	-61.2	-3.457	-57.5	-4.581	-62.7	-4.809	-54.5	-4.876	-51.6
LT	0.909	15.8	0.308	9.1	0.221	7.5	0.712	16.6	0.691	17.5	0.739	16.8
Wk	-0.501	-5.9	-0.273	-5.1	-0.180	-3.8	-0.332	-4.4	-0.305	-4.3	-0.473	-5.0
Structural parameter												
TR_D_M	0.773	17.0	1.396	-23.3	1.400	-23.7	0.810	16.7	0.811	16.7	0.809	16.9
Attraction term												
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a
Car availability												
AD2pVeh	1.334	40.3	1.209	50.2	1.050	48.2	1.098	46.8	1.287	33.2	1.288	32.3
AP1Veh	1.596	25.5	1.290	24.9	1.193	25.2	1.421	27.8	1.628	24.6	1.623	24.7
AP2pVeh	2.017	30.2	1.659	30.5	1.499	30.1	1.781	33.4	2.058	27.8	2.052	27.9
Scale parameters												
1986scale					1.192	26.1	1.173	21.8				
86costscale									1.120	5.4	1.060	2.0
86losscale									1.217	20.4	1.227	15.7
86constscale									1.020	1.6	0.930	1.3
86socioeconscale									0.944	1.9	0.944	1.6
1986 mode constants												
AP_86							-4.312	-56.5			-5.255	-16.6
LT_86							0.577	16.3			0.723	11.3
Wk_86							-0.246	-3.8			-0.249	-3.0

Table B.4: Pooled 1996 & 2006 models

	1996 model		Pooled 1		Pooled 2		Pooled 3		Pooled 4		Pooled 5	
Log-likelihood		-366,987.3		-596,787.4		-596,634.7		-596,647.2		-596,662.9		-596,627.1
gain w.r.t. Pooled 1		n/a				152.7		140.2		124.6		160.3
Observations		60,241		94,927		94,927		94,927		94,927		94,927
LL per obs		-6.092		-6.287		-6.285		-6.285		-6.285		-6.285
Cost parameters												
LogCost	-0.493	-33.0	-0.259	-22.8	-0.265	-24.7	-0.291	-27.2	-0.289	-25.8	-0.312	-24.4
Cost	0.000	-7.5	-0.001	-29.9	-0.001	-24.8	-0.001	-19.2	-0.001	-19.2	-0.001	-17.6
Level of service												
CarTime	-0.034	-42.5	-0.035	-50.4	-0.033	-50.2	-0.035	-50.1	-0.035	-49.5	-0.035	-47.4
TranIVT	-0.025	-38.8	-0.023	-46.0	-0.021	-44.8	-0.022	-44.9	-0.022	-43.6	-0.021	-42.1
TranWait	-0.043	-29.0	-0.046	-33.3	-0.044	-34.6	-0.044	-33.6	-0.045	-34.3	-0.043	-33.2
TranWalk	-0.025	-11.2	-0.024	-20.5	-0.020	-18.7	-0.021	-19.0	-0.020	-17.7	-0.021	-18.6
APDist	-0.022	-33.5	-0.026	-43.2	-0.023	-41.4	-0.024	-40.3	-0.024	-40.5	-0.023	-38.5
WalkDist	-0.615	-47.0	-0.574	-60.8	-0.532	-59.2	-0.538	-58.3	-0.546	-56.7	-0.526	-53.3
Destination terms												
CBDDest	0.573	18.3	0.092	4.2	0.054	2.7	0.051	2.5	0.039	1.9	0.039	1.8
CBDLT	0.141	3.7	0.646	20.9	0.639	22.3	0.657	22.7	0.649	22.7	0.612	16.4
Mode constants												
AP	-5.240	-57.0	-4.066	-57.5	-3.845	-57.3	-4.116	-57.5	-4.065	-51.1	-4.275	-49.2
LT	0.909	15.8	0.664	17.2	0.571	15.9	0.427	10.5	0.596	16.5	0.443	10.5
Wk	-0.501	-5.9	0.488	7.7	0.379	6.5	-0.051	-0.7	0.118	1.9	-0.187	-2.1
Structural parameter												
TR_D_M	0.773	17.0	0.836	13.4	0.837	13.1	0.803	16.1	0.816	15.1	0.803	16.2
Attraction term												
TotEmp	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a	1.000	n/a
Car availability												
AD2pVeh	1.334	40.3	1.395	52.3	1.292	51.3	1.296	51.0	1.398	35.5	1.345	34.0
AP1Veh	1.596	25.5	1.546	29.1	1.430	28.8	1.453	29.0	1.529	25.6	1.506	24.9
AP2pVeh	2.017	30.2	1.963	35.0	1.821	34.6	1.845	34.8	1.952	29.1	1.914	28.1
Scale parameters												
2006scale					1.123	19.1	1.124	15.9				
06costscale									1.152	6.5	1.024	0.8
06losscale									1.095	10.1	1.158	11.8
06constscale									1.148	10.3	1.272	2.7
06socioeconscale									1.010	0.3	1.067	1.8
2006 mode constants												
AP_06							-4.159	-56.1			-3.616	-12.3
LT_06							0.701	18.1			0.613	9.8
Wk_06							0.209	3.2			0.227	3.7

Table B.5: 1986 models with distributed cost and car time terms

	HW_MD_1986_C_DS_MNL MNL spec. C		HW_MD_1986_C_DS_EC40 Triangular EC terms 100 Halton draws		Percentage change	
					Param.	t-ratio
Log-likelihood		-285,610.7		-285,499.1		
gain				111.6		
Observations		50,254		50,254		
Cost parameters						
Cost	-0.0010	-12.7	-0.0015	-17.7	56.6%	38.9%
CostTri			0.0015	n/a		
LogCost	-0.3004	-23.6	-0.1759	-10.9	-41.4%	-53.6%
Level of service						
CarTime	-0.033	-77.6	-0.037	-65.4	12.6%	-15.7%
AutoTimTri			-0.035	-21.7		
TranIVT	-0.022	-60.2	-0.022	-60.1	0.1%	-0.2%
TranWait	-0.060	-24.5	-0.062	-24.9	2.6%	1.7%
TranWalk	-0.025	-16.1	-0.027	-16.7	4.8%	3.9%
APDist	-0.020	-27.0	-0.020	-26.2	-3.7%	-2.7%
WalkDist	-0.584	-45.0	-0.585	-44.9	0.2%	0.0%
Destination terms						
CBDDest	0.392	13.9	0.408	14.4	4.0%	3.6%
CBDLT	0.189	5.1	0.170	4.6	-10.1%	-10.4%
Mode constants						
AP	-3.940	-44.6	-3.572	-38.0	-9.3%	-14.8%
LT	0.970	20.4	0.842	17.0	-13.1%	-16.5%
Wk	0.248	2.8	0.617	6.7	149.1%	135.4%
Car availability						
AD2pVeh	1.298	42.1	1.335	42.3	2.9%	0.5%
AP1Veh	1.474	20.9	1.566	21.7	6.2%	3.7%
AP2pVeh	1.889	26.2	2.017	27.1	6.8%	3.7%
Socio economics						
ADAge1617	-2.101	-6.2	-2.106	-6.2	0.2%	-0.8%
ADAge1825	-0.834	-24.7	-0.845	-24.7	1.3%	-0.1%
ADAge2630	-0.167	-4.8	-0.178	-5.1	6.6%	5.1%
ADMale	1.016	38.3	1.010	37.6	-0.6%	-1.8%
WkMale	0.215	3.4	0.219	3.5	2.1%	1.9%
Attraction term						
TotEmp	1.000	n/a	1.000	n/a		

Table B.6: 2006 models with distributed cost and car time terms

	HW_MD_2006_C_DS_MNL2 MNL spec. C		HW_MD_2006_C_DS_EC5 Triangular EC terms 90 Halton draws		Percentage change Param.	t-ratio
Log-likelihood		-388,455.2		-388,320.9		
gain				134.4		
Observations		50,254		50,254		
Cost parameters						
Cost	-0.0012	-21.2	-0.0016	-32.4	35.6%	53.1%
CostTri			0.0016	n/a		
LogCost	-0.255	-16.6				
Level of service						
AutoTime	-0.031	-68.8	-0.034	-75.1	9.1%	9.1%
AutoTimTri			-0.002	-26.2		
TranIVT	-0.018	-50.4	-0.018	-50.4	0.0%	0.0%
TranWait	-0.050	-28.0	-0.051	-28.6	2.3%	2.1%
TranWalk	-0.022	-17.2	-0.022	-17.5	1.9%	1.9%
APDist	-0.025	-35.9	-0.024	-34.7	-4.7%	-3.4%
WalkDist	-0.532	-54.3	-0.531	-54.3	-0.1%	-0.1%
Destination Terms						
CBDDest	-0.147	-6.3	-0.126	-5.4	-14.1%	-14.0%
CBDLT	0.873	23.7	0.851	23.1	-2.6%	-2.5%
Mode constants						
AP	-3.480	-41.0	-2.571	-39.3	-26.1%	-4.2%
LT	0.853	18.8	0.765	16.9	-10.4%	-9.8%
Wk	0.764	9.6	1.648	27.5	115.7%	187.4%
Car Availability						
AD2pVeh	1.553	47.3	1.553	47.3	0.0%	-0.1%
AP1Veh	1.433	22.4	1.427	22.3	-0.4%	-0.6%
AP2pVeh	1.849	27.7	1.840	27.5	-0.5%	-0.7%
Socio economics						
ADAge1617	-3.005	-5.7	-3.000	-5.6	-0.2%	-0.6%
ADAge1825	-1.342	-32.1	-1.343	-32.0	0.0%	-0.1%
ADAge2630	-0.343	-8.3	-0.343	-8.3	0.0%	-0.1%
ADMale	0.869	33.6	0.867	33.5	-0.2%	-0.3%
WkMale	0.108	1.9	0.105	1.9	-3.3%	-3.4%
Attraction term						
TotEmp	1.000	n/a	1.000	n/a		

Appendix C

Sydney model results

The following tables present the model parameter values. In the tables, in each column the parameter value β is presented on the left and the t-ratio for the parameter is presented on the right. The t-ratio is given by the ratio β/σ where σ is the standard deviation of the parameter estimate. For model parameters, the t-ratios define the significance of the parameter relative to a value of zero. For the structural parameters and the scale parameters the t-ratios have been presented relative to a value of one.

The cost parameters are presented in 1991 prices and values. For the 1996, 2001 and 2006 models this means that the cost parameters have been adjusted to take account of real income growth using the procedure documented in Section 5.1.1.

The 1991 parameters values are presented after rescaling to take account of differences in model scale between the 1991 and 2006 datasets, following the procedure described in Section 5.2.

Table C.1: Sydney commute model results, sparse specification

	COM_A3_91		COM_A_0408	
Log-likelihood		-29,979.8		-34,510.5
Observations		5,111		5,173
LL per obs		-5.866		-6.671
Cost parameters				
LogCost	-0.461	-11.1	-0.341	-8.9
Cost	-0.0004	-3.4	-0.0003	-3.3
Level of service				
CarTime	-0.027	-26.9	-0.030	-31.4
RlTime	-0.012	-10.3	-0.014	-13.0
BusTime	-0.022	-13.5	-0.021	-15.9
AccTime	-0.028	-9.8	-0.014	-6.2
FrWtTm	-0.021	-3.2	-0.020	-4.2
OtWTme	-0.046	-8.5	-0.044	-10.0
CarPDist	-0.017	-6.5	-0.023	-6.5
BkDist	-0.167	-7.5	-0.162	-7.4
WlkDist	-0.605	-21.1	-0.606	-21.0
Destination terms				
Intra	-0.162	-1.8	0.227	2.0
CBDDest	-0.167	-1.6	-0.452	-5.0
CBDRail	0.873	6.3	1.328	10.8
CBDBus	0.461	2.7	1.264	9.1
Mode constants				
CrP	-3.620	-16.8	-2.604	-24.8
Trn	-0.865	-4.8	-0.710	-5.5
Bus	-1.460	-7.2	-1.057	-8.6
Bk	-7.525	-12.9	-4.779	-14.3
Wk	-1.371	-4.7	-0.162	-0.9
Tx	-5.431	-9.4	-4.285	-15.0
Structural parameter				
TR_M_D	0.737	3.6	1.000	n/a
Attraction term				
TotEmp	1.000	n/a	1.000	n/a

Table C.2: Sydney commute model results, car avail specification

	COM_B3_91		COM_B_0408	
Log-likelihood		-29,691.6		-34,230.9
Observations		5,111		5,173
LL per obs		-5.809		-6.617
Cost parameters				
LogCost	-0.444	-10.8	-0.329	-8.5
Cost	-0.0004	-3.2	-0.0003	-3.0
Level of service				
CarTime	-0.027	-27.2	-0.031	-31.8
RlTime	-0.012	-10.1	-0.013	-12.4
BusTime	-0.022	-13.3	-0.020	-15.2
AccTime	-0.026	-9.1	-0.012	-5.6
FrWtTm	-0.016	-2.4	-0.014	-3.0
OtWTme	-0.044	-8.3	-0.044	-10.0
CarPDist	-0.017	-6.4	-0.023	-6.3
BkDist	-0.163	-7.4	-0.160	-7.4
WlkDist	-0.588	-21.1	-0.599	-20.9
Destination terms				
Intra	-0.143	-1.6	0.275	2.4
CBDDest	-0.176	-1.7	-0.477	-5.3
CBDRail	0.891	6.6	1.370	11.1
CBDBus	0.471	2.8	1.270	9.2
Mode constants				
CrP	-5.903	-13.9	-4.296	-17.6
Trn	-1.839	-8.4	-1.267	-9.2
Bus	-2.424	-9.6	-1.606	-12.3
Bk	-8.255	-13.3	-5.152	-15.3
Wk	-2.207	-6.6	-0.558	-3.2
Tx	-6.291	-10.1	-4.727	-16.4
Structural parameter				
TR_M_D	0.726	17.8	1.000	n/a
Attraction term				
TotEmp	1.000	n/a	1.000	n/a
Car availability				
CarComp	-2.028	-13.1	-1.468	-19.3
CmpCrDr	0.823	6.0	0.678	7.0
PassOpts	1.754	6.0	1.546	6.5

Table C.3: Sydney commute model results, detailed specification

	COM_C3_91		COM_C_0408	
Log-likelihood		-29,590.5		-34,182.9
Observations		5,111		5,173
LL per obs		-5.790		-6.608
Cost parameters				
LogCost	-0.445	-11.2	-0.248	-8.4
Cost	-0.0003	-3.2	-0.0002	-2.8
Level of service				
CarTime	-0.027	-28.2	-0.031	-32.0
RlTime	-0.012	-10.2	-0.013	-12.1
BusTime	-0.022	-13.8	-0.021	-15.4
AccTime	-0.026	-9.4	-0.012	-5.6
FrWtTm	-0.014	-2.3	-0.014	-2.9
OtWTme	-0.044	-8.6	-0.043	-9.9
CarPDist	-0.017	-6.6	-0.023	-6.3
BkDist	-0.162	-7.7	-0.159	-7.4
WlkDist	-0.588	-21.7	-0.599	-20.9
Destination terms				
Intra	-0.146	-1.7	0.271	2.4
CBDDest	-0.179	-1.8	-0.484	-5.4
CBDRail	0.901	6.9	1.383	11.2
CBDBus	0.489	3.0	1.306	9.4
Mode constants				
CrP	-5.676	-14.0	-4.294	-17.3
Trn	-3.145	-10.1	-1.773	-10.8
Bus	-2.236	-9.2	-1.604	-11.7
Bk	-10.168	-10.9	-6.598	-11.4
Wk	-1.997	-6.2	-0.544	-3.0
Tx	-6.089	-10.2	-4.765	-16.2
Structural parameter				
TR_M_D	0.729	17.8	1.000	n/a
Attraction term				
TotEmp	1.000	n/a	1.000	n/a
Car availability				
CarComp	-2.029	-13.5	-1.481	-19.3
CmpCrDr	0.831	6.2	0.691	7.1
PassOpts	1.732	6.1	1.558	6.6
Socio-economic				
Ageu24CrD	-0.862	-6.0	-0.473	-4.2
MaleCrDr	0.752	6.8	0.197	2.6
FullTmRl	1.324	6.2	0.131	1.3
HiPersInc	0.758	5.7	0.683	6.9
MaleBike	3.169	4.2	2.093	3.9

Table C.4: Sydney home–other travel model results, sparse specification

	OTH_A3_91		OTH_A_0408	
Log-likelihood		-47,715.9		-53,849.2
Observations		10,644		10,464
LL per obs		-4.483		-5.146
Cost parameters				
LogCost	-1.371	-35.6	-0.713	-34.1
Level of service				
CarTime	-0.045	-34.6	-0.066	-51.4
RlTime	-0.021	-8.1	-0.016	-7.6
BusTime	-0.020	-8.0	-0.028	-10.8
AccTime	-0.046	-9.0	-0.014	-4.2
WaitTime	-0.029	-5.2	-0.025	-5.3
CarPDist	0.005	3.5	0.013	7.3
BkDist	-0.332	-14.1	-0.320	-13.7
WlkDist	-0.750	-48.2	-0.927	-50.8
Destination terms				
Intra	-0.222	-4.6	-0.170	-4.2
CBDDest	-1.328	-10.5	-1.488	-10.8
CBDRail	1.948	8.2	1.701	7.1
CBDBus	1.601	6.6	1.189	4.0
Mode constants				
CrP	-4.669	-18.0	-6.267	-16.1
Trn	-6.003	-8.2	-6.114	-11.9
Bus	-5.521	-8.3	-5.604	-11.5
Bk	-14.808	-17.3	-9.941	-16.9
Wk	-5.564	-15.7	-2.771	-11.7
Tx	-9.450	-9.5	-8.998	-12.4
Structural parameter				
TR_M_D	0.499	15.3	0.650	10.0
Attraction terms				
L_S_M	1.000	n/a	1.000	n/a
ServEmp	4.610	45.4	6.611	45.4

Table C.5: Sydney home–other travel model results, car avail specification

	OTH_B3_91		OTH_B_0408	
Log-likelihood		-47,326.0		-53,849.2
Observations		10,644		10,464
LL per obs		-4.446		-5.146
Cost parameters				
LogCost	-1.105	-32.3	-0.713	-34.1
Level of service				
CarTime	-0.052	-41.7	-0.066	-51.4
RlTime	-0.022	-8.3	-0.016	-7.6
BusTime	-0.022	-8.8	-0.028	-10.8
AccTime	-0.042	-8.2	-0.014	-4.2
WaitTime	-0.027	-4.9	-0.025	-5.3
CarPDist	0.005	3.4	0.013	7.3
BkDist	-0.323	-14.0	-0.320	-13.7
WlkDist	-0.720	-47.8	-0.927	-50.8
Destination terms				
Intra	-0.006	-0.1	-0.170	-4.2
CBDDest	-0.326	-2.5	-1.488	-10.8
CBDRail	0.833	3.5	1.701	7.1
CBDBus	0.445	1.8	1.189	4.0
Mode constants				
CrP	-10.210	-13.8	-6.267	-16.1
Trn	-8.685	-9.3	-6.114	-11.9
Bus	-8.003	-9.2	-5.604	-11.5
Bk	-16.058	-15.0	-9.941	-16.9
Wk	-6.234	-13.1	-2.771	-11.7
Tx	-12.547	-10.1	-8.998	-12.4
Structural parameter				
TR_M_D	0.450	16.9	0.582	11.8
Attraction term				
L_S_M	1.000	n/a	1.000	n/a
ServEmp	6.010	45.3	6.594	45.3
Car availability				
CarComp	-1.318	-7.3	-0.756	-6.7
PassOpts	5.335	11.5	3.159	12.3

Table C.6: Sydney home–other travel model results, detailed specification

	OTH_C3_91		OTH_C_0408	
Log-likelihood		-46,935.0		-53,403.8
Observations		10,644		10,464
LL per obs		-4.410		-5.104
Cost parameters				
LogCost	-1.124	-32.1	-0.700	-33.2
Level of service				
CarTime	-0.053	-41.8	-0.066	-51.4
RlTime	-0.022	-8.0	-0.016	-7.5
BusTime	-0.023	-9.0	-0.029	-10.9
AccTime	-0.040	-7.6	-0.015	-4.2
WaitTime	-0.024	-4.3	-0.025	-5.2
CarPDist	0.005	3.6	0.014	8.0
BkDist	-0.331	-14.0	-0.319	-13.7
WlkDist	-0.736	-47.8	-0.927	-50.8
Destination terms				
Intra	-0.006	-0.1	-0.163	-4.0
CBDDest	-0.341	-2.5	-1.497	-10.9
CBDRail	0.887	3.6	1.707	7.1
CBDBus	0.448	1.8	1.199	4.1
Mode constants				
CrP	-10.799	-12.7	-6.347	-15.7
Trn	-10.115	-9.1	-5.911	-11.3
Bus	-8.772	-8.7	-5.329	-10.5
Bk	-19.697	-12.7	-11.373	-14.7
Wk	-6.267	-12.0	-2.271	-10.6
Tx	-13.562	-9.5	-8.583	-12.1
Structural parameter				
TR_M_D	0.416	17.8	0.581	11.8
Attraction term				
L_S_M	1.000	n/a	1.000	n/a
ServEmp	6.038	45.2	6.570	45.2
Car availability				
CarComp	-1.594	-7.5	-0.812	-7.1
PassOpts	5.308	10.4	2.762	11.2
Socio-economic				
CarPMale	-1.825	-8.4	-0.481	-4.6
BusMale	-1.301	-3.2	-0.274	-1.0
BikeMale	4.190	5.3	2.939	6.0
CarP¡10	4.374	10.8	3.279	14.1
CarP60pl	1.049	4.1	0.518	3.8
PT10to19	-1.082	-2.4	-0.305	-1.1
PT60pl	3.285	7.9	0.881	3.8

Appendix D

Destination sampling

The theory for estimation of multinomial logit models using destination sampling was set out in McFadden (1978), and the equations that explain how the process operates are given in Ben-Akiva and Lerman (1985). McFadden showed that under the *positive conditioning* property (the condition that the probability of each alternative being sampled is positive), asymptotically consistent estimates of model parameters can be obtained if a modified log likelihood function is maximised:

$$LL = log\left(\frac{exp(V_c + log\,\pi(D|c))}{\sum_{j\in D} exp(V_D + log\,\pi(D|j))}\right) \tag{D.1}$$

where: V_j is the systematic part of utility for alternative j

c is the chosen alternative

D is the sampled set of alternatives, a subset of the set of all available alternatives C

$\pi(D|j)$ is the probability of sampling D, if j is the chosen alternative

The positive conditioning property is that $\pi(D|j) > 0 \; \forall j \in D$. It is essential that the chosen alternative c is included in D.

To perform *independent importance sampling*, $C-1$ draws are made, one for each alternative j except for the chosen alternative c, selecting each alternative with probability q_j, and then adding the chosen alternative to the choice set. The sample of alternatives that results has the following probability distribution:

$$\pi(D|i) = \prod_{j \in D,\ j \neq i} q_i \prod_{j \neq D} (1 - q_j) \tag{D.2}$$

$$\pi(D|i) = 1/q(i)\ Q(D) \tag{D.3}$$

where: $Q(D) = \prod_{j \in D} q_j \prod_{j \neq D} (1 - q_j)$

Substituting Equation D.3 into Equation D.1 gives:

$$LL = log \left(\frac{exp(V_c - log(q_c))}{\sum_{j \in D} exp(V_D - log(q_j))} \right) \tag{D.4}$$

Ben-Akiva and Lerman (1985) suggested a simple negative exponential model to allow the calculation of q_j:

$$q_j \propto S_j exp(-\varphi d_j) \tag{D.5}$$

where: S_j is the attraction variable

φ is a parameter

d_j is the distance to destination j

Following Ben-Akiva and Lerman a value for α of $2/\overline{d}$, where $\overline{d}$ is the mean tour distance, has been used.

To operationalise Equation D.5, the weights for each zone are expressed relative to a *key zone* by calculating:

$$q_j = min(w_j/w_k, 1) \tag{D.6}$$

$$w_j = S_j exp(-\varphi d_j) \tag{D.7}$$

The key zone is determined by ranking the zones by w_j, and then key zone k is then the k^{th} most attractive zone. It should be noted that the implication of Equation D.6 is that all zone ranks up to k are included in the sample as $q_j = 1$ if $w_j > w_k$. Scaling the weights also ensures that all zones have reasonable probability values.

A measure of the accuracy of different destination samples is provided by determining the coverage of the sampled choice set, calculated as an average over the N observations in the sample:

$$W = \sum_{N} \left(\sum_{D} w_j / \sum_{C} w_j \right) /N \tag{D.8}$$

As W approaches 1, the accuracy of the sample approaches achieved by modelling the full sample.

Models using destination sampling were estimated for both the 1986 and 2006 Toronto datasets, as these are the two datasets that have been used for the mixed logit analysis. For the 1986 data the total number of destination alternatives C is 1404, whereas for the 2006 data the $C = 1845$.

Generation of 1986 destination sample

Table D summarises the results from tests using different key zones to determine a destination sample size giving an acceptable level of coverage for the 1986 data.

The tests were undertaken using a modified version of model specification C, defined in Table 4.2 in Section 4.2.2. The modified was that the model was converted into a multinomial specification.

Table D.1: 1986 destination sample size tests

k	$max(D)$	$\overline{D}$	W	$max(D)/C$
50	212	151.6	76.0%	15.1%
60	229	167.3	79.0%	16.3%
80	258	195.0	83.6%	18.4%
100	294	221.0	86.7%	20.9%
120	324	245.2	89.0%	23.1%
125	325	251.1	89.5%	23.1%
130	325	257.1	90.0%	23.1%
140	337	268.5	90.9%	24.0%

On the basis of these tests, a destination sample D of 325 alternatives was used with a key zone of 130. This sample achieved 90% coverage using just under one-quarter of the 1404 destinations. Table D demonstrates that the impact of destination sampling on the model parameters is very small, with an RMS measure calculated for the change in parameter value relative to a model estimated without destination sampling of just 0.06%.

Table D.2: Impact of destination sampling on 1986 model parameters

	all 1404 dest.s		235 dest. sample		param.s	differences
Log-likelihood		-306,427.2		-285,610.7		
Observations		50,254		50,254		
Cost parameters						
LogCost	-0.3004	-23.6	-0.3004	-23.6	0.0000	0.00
Cost	-0.0010	-12.7	-0.0010	-12.7	0.0000	0.01
Level of service						
CarTime	-0.0329	-77.6	-0.0329	-77.6	0.0000	-0.02
TranIVT	-0.0222	-60.3	-0.0222	-60.2	0.0000	0.00
TranWait	-0.0603	-24.5	-0.0603	-24.5	0.0000	0.00
TranWalk	-0.0254	-16.1	-0.0254	-16.1	0.0000	-0.01
APDist	-0.0205	-27.0	-0.0204	-27.0	0.0000	0.02
WalkDist	-0.5837	-45.0	-0.5837	-45.0	0.0000	0.00
Destination terms						
CBDDest	0.3918	13.9	0.3923	13.9	0.0005	0.01
CBDLT	0.1888	5.1	0.1889	5.1	0.0001	0.00
Mode constants						
AP	-3.9405	-44.6	-3.9403	-44.6	0.0002	0.00
LT	0.9698	20.4	0.9695	20.4	-0.0002	0.00
Wk	0.2475	2.8	0.2476	2.8	0.0001	0.00
Attraction term						
TotEmp	1.0000	n/a	1.0000	n/a	0.0000	n/a
Car availability						
AD2pVeh	1.2977	42.0	1.2979	42.1	0.0003	0.01
AP1Veh	1.4742	20.9	1.4736	20.9	-0.0006	-0.01
AP2pVeh	1.8900	26.2	1.8894	26.2	-0.0006	-0.01
Socio economics						
ADAge1617	-2.104	-6.2	-2.101	-6.2	0.0029	0.01
ADAge1825	-0.834	-24.7	-0.834	-24.7	-0.0005	-0.01
ADAge2630	-0.167	-4.8	-0.167	-4.8	0.0000	0.00
ADMale	1.016	38.4	1.016	38.3	-0.0002	-0.01
WkMale	0.215	3.4	0.215	3.4	-0.0002	0.00
				RMS:	0.06%	

Generation of 2006 destination sample

Table D summarises the results from tests using different key zones to determine a destination sample size giving an acceptable level of coverage for the 1986 data.

Table D.3: 1986 destination sample size tests

k	$max(D)$	$\overline{D}$	W	$max(D)/C$
50	263	186.1	70%	14.3%
60	278	203.5	72%	15.1%
80	304	235.9	77%	16.5%
100	344	265.9	81%	18.6%
120	376	294.3	83%	20.4%
140	407	320.7	85%	22.1%
160	441	345.7	87%	23.9%
180	471	370.0	89%	25.5%
190	481	382.1	89%	26.1%
200	492	394.2	90%	26.7%

On the basis of these tests, a destination sample D of 492 alternatives was used with a key zone of 200. This sample achieved 90% coverage using just over one-quarter of the 1845 destinations. Table D demonstrates that the impact of destination sampling on the model parameters is very small, with an RMS measure calculated for the change in parameter value relative to a model estimated without destination sampling of just 0.06%.

Table D.4: Impact of destination sampling on 2006 model parameters

	all 1845 dest.s		492 dest. sample		param.s	differences
Log-likelihood		-411,904.1		-394,123.3		
Observations		64,808		64,808		
Cost parameters						
LogCost	-0.1976	-16.6	-0.1975	-16.6	0.0000	0.00
Cost	-0.0012	-21.2	-0.0012	-21.2	0.0000	0.01
Level of service						
CarTime	-0.0312	-68.8	-0.0312	-68.9	0.0000	-0.02
TranIVT	-0.0181	-50.4	-0.0181	-50.4	0.0000	-0.02
TranWait	-0.0495	-28.0	-0.0495	-28.0	0.0000	0.01
TranWalk	-0.0215	-17.2	-0.0215	-17.2	0.0000	0.00
APDist	-0.0253	-35.9	-0.0253	-35.9	0.0000	0.02
WalkDist	-0.5318	-54.3	-0.5318	-54.3	0.0000	0.00
Destination terms						
CBDDest	-0.1467	-6.3	-0.1466	-6.3	0.0001	0.00
CBDLT	0.8734	23.7	0.8734	23.7	0.0001	0.00
Mode constants						
AP	-3.4282	-41.3	-3.4277	-41.3	0.0006	0.00
LT	0.8530	18.8	0.8532	18.8	0.0002	0.00
Wk	0.8154	10.5	0.8158	10.5	0.0004	0.00
Attraction term						
TotEmp	1.0000	n/a	1.0000	n/a	0.0000	n/a
Car availability						
AD2pVeh	1.5528	47.3	1.5532	47.3	0.0005	0.01
AP1Veh	1.4324	22.4	1.4317	22.4	-0.0006	-0.01
AP2pVeh	1.8485	27.7	1.8483	27.7	-0.0003	0.00
Socio economics						
ADAge1617	-3.011	-5.7	-3.008	-5.7	0.0030	0.00
ADAge1825	-1.342	-32.1	-1.341	-32.1	0.0006	0.01
ADAge2630	-0.343	-8.3	-0.343	-8.3	-0.0001	0.00
ADMale	0.869	33.6	0.868	33.6	-0.0002	-0.01
WkMale	0.108	1.9	0.108	1.9	-0.0002	0.00
				RMS:	0.06%	