Zenith Model of Victoria

Technical Note 7
Mode Choice

Zenith Version 2.0.0

VEITCH LISTER CONSULTING PTY LTD

Date: 05-02-2012

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Date	Revision	Prepared By	Checked By	Approved By	Description
17-03-2011	A	TV	AA	MV	Draft
12-04-2011	B	TV	AA	MV	Revision, addressing comments from DOT
05-02-2012	C	TV	AA	MV	Final Report

Contents

1 Introduction

The Zenith travel model of Victoria is one of a family of models developed by Veitch Lister Consulting (VLC) for transport planning in Australian cities and regions.

This document is one in a series of technical notes that collectively describe the Zenith Model of Victoria.

1.1 Related Documents

This technical note is the seventh of eleven. The other technical notes are:

- Working Paper 1: Model Validation Framework and Data Sources
- Working Paper 2: Review of VISTA07
- Working Paper 3: Home Based Trip Production Model
- Working Paper 4: Non-Home Based Trip Production Model
- Working Paper 5: Household Segmentation & Travel Market Segmentation Models
- Working Paper 6: Period Allocation and Vehicle Occupancy Models
- Working Paper 7: Mode Choice Model
- Working Paper 8: Destination Choice and Trip Attraction Model
- Working Paper 9: Overall Model Validation
- Working Paper 10: Backcasting and Sensitivity Testing
- Working Paper 11: Reference Case Model Assumptions

1.2 Scope of This Document

The primary focus of this document is the Mode Choice model, though the scope of our analysis has included the estimation of a large number of route choice modelling assumptions, such as public transport access penalties, transfer penalties, time weights, etc.

The scope of our recalibration has at this stage been limited to Home Based Work trips. Given the importance of Home Based Work as a driver of public transport demands (Home Based Work trips are responsible for 65% of all peak public transport passenger kilometres), it was felt that a robust model of Home Based Work would provide greater value, and greater understanding, than a crude model of all trip purposes.

This decision was also supported by two other factors:

1. During our initial recalibration of the Home Based Work market (using the traditional Zenith modelling approach) we found a number of areas where the model could be significantly improved through a more robust approach.

2. This approach would also provide estimates of access penalties by mode, transfer penalties (by mode to mode pair), in vehicle time weights, weights on waiting time, walking time, car travel time; would measure the effect of station parking, smart bus improvements, fuel prices and tolls on mode choice. We were also able to include cycling as a mode of transport for the first time.

By accounting for these factors, we were also able to identify a significant number of other areas of potential improvement. These have been discussed at length in Section 4.1.3 - Model Validation.

The remainder of this document is structured as follows:

- Section 2 describes the data sources available for recalibration,

- Section 3 describes our methodology, and

- Section 4 describes the results of the recalibrated Mode Choice model.

2 Data Sources

The primary source of information used in to calibrate the Mode Choice model was the Victorian Integrated Survey of Travel and Activity 2007 (VISTA07). Version 1.3.1 of VISTA07 was made available to VLC. This survey was used to estimate model parameters, and to validate the resulting model at various levels of aggregation.

The VISTA07 sample comprises 43,822 people, from 17,715 households. In total there are 128,744 reported trips, a very healthy sample from which to estimate a strategic travel model.

Not all of the survey responses are usable for our purposes. In the case of mode choice, trips must have their origin and destination within the Zenith model area to be of use (the model does not currently cover Shepparton and the LaTrobe Valley). Travel made on weekends and public holidays and during school holidays were also excluded. That leaves a sample of 8,540 households (48% of the total sample); still a very healthy sample from which to calibrate a model.

3 Methodology

3.1 Theoretical Background

The Zenith Mode Choice model employs a nested logit model.

A conceptual explanation of this model is now provided.

3.1.1 The Logit Model

In a transport modelling context, choice models (such as logit) are employed to predict the travel choices made by individuals under a wide range of real and hypothetical circumstances.

In the case of mode choice (as it is applied in Zenith), individuals may choose from a set of available travel modes; typically car, walking, cycling, or public transport, given a known origin, destination, departure time, etc.

Each individual is assumed to derive a certain amount of *utility* from each alternative mode, where utility can be thought of as "value" or "usefulness". Travel cost is generally thought of as the opposite of utility.

Furthermore, it is assumed that each individual chooses the mode which provides them with the *greatest utility*. We say that individuals are "utility maximisers".

The exact utility derived by an individual from a specific travel mode depends on a range of factors. Generally, these can be grouped as follows:

- Factors relating to the travel alternative (mode) (eg. in the case of a public transport mode, in-vehicle travel time, waiting time, fare, walking time, number of transfers, reliability, etc)
- Factors relating to the individual making the choice (eg. car availability, income, occupation, fitness, as well as tastes and preferences held by the individual towards each mode, etc)
- External factors (eg. day of the week, the weather, strikes, etc)

It is impossible for us to know all of these factors, particularly those relating to individual tastes and preferences. It would be impractical to ask each individual in Melbourne about their preferences towards certain modes, and even if we did, the best that we could do is to improve our estimate of each individual's utility. The actual, exact, utility derived by each individual would remain a mystery.

Given that the actual utility derived by an individual is unknowable, the best that we can do is to construct a *probability distribution*.

Our probability distribution is composed of two parts:

1. An estimate of the utility, *V*, based on the *known, observable* factors relating to the travel mode, the individual, and externalities, and
2. A random error term, ε, which captures the effect of all of the *unknown* and *unobservable* factors.

In mathematical terms,

$$U = V + \varepsilon$$

It is the random error term, **ε**, which gives utility its distribution.

Obviously, it is our aim as modellers to make our *estimate of utility* (component 1) as accurate as possible, by including in the model as many of the key factors which affect an individual's utility as possible. By doing this, we try reduce the number of unknown factors, and reduce the spread of the random error (component 2), thus keeping the probability distribution narrow. In essence, this allows us to make accurate and confident predictions about people's choices.

An example is shown in Figure 1 below. In the example, the probability distributions for car and public transport utility are represented by the solid blue and red lines. The probability distribution for car sits to the right of public transport, which means that car is likely to have a higher utility. Given that people maximise their utility, a majority of people will choose car, in this example.
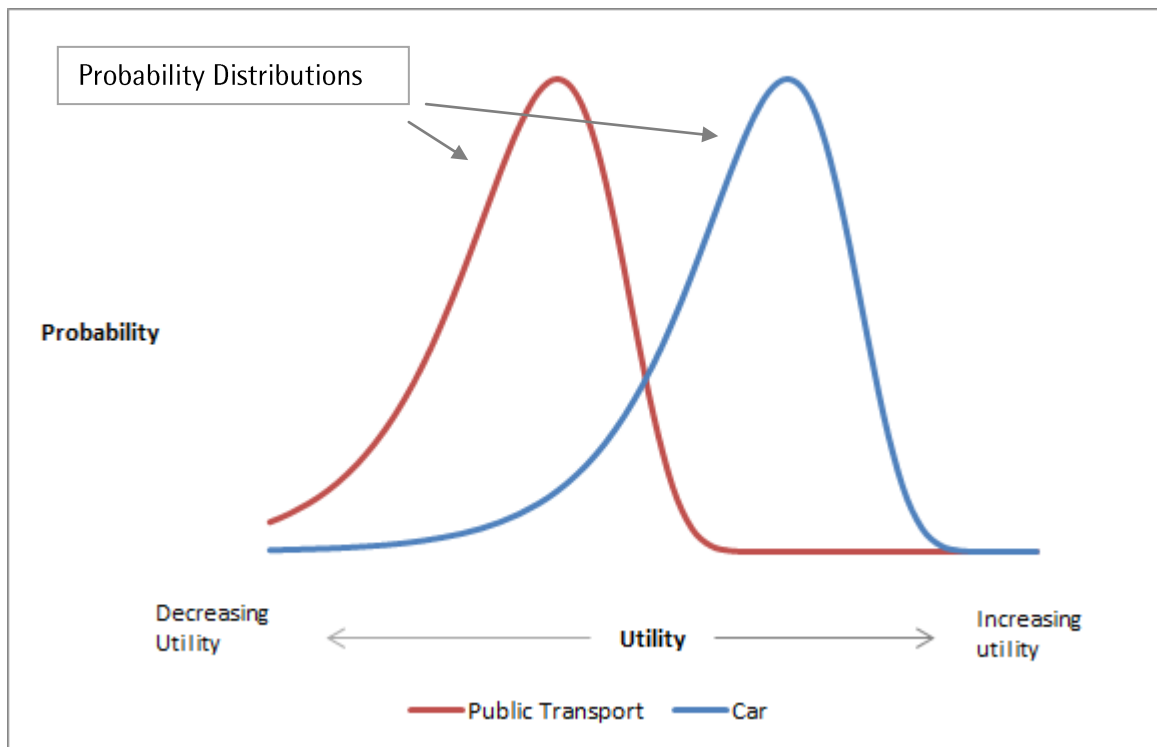

Figure 1 - Example Probability Distributions of Car and Public Transport Utility

Now, it is important to understand that for an actual individual, there is no probability distribution. An individual derives a specific utility from both car and public transport, and chooses the mode which offers the highest utility. The problem is that we can never find out what these utilities are. The probability distribution, therefore, is merely our *estimate* of their utility.

To see how this applies to an individual, consider Figure 2 below. The Figure shows the actual utility derived by a hypothetical individual from car and public transport alternatives. The individual's utility for car is higher than their utility for public transport – as such, this individual will choose to travel by car.
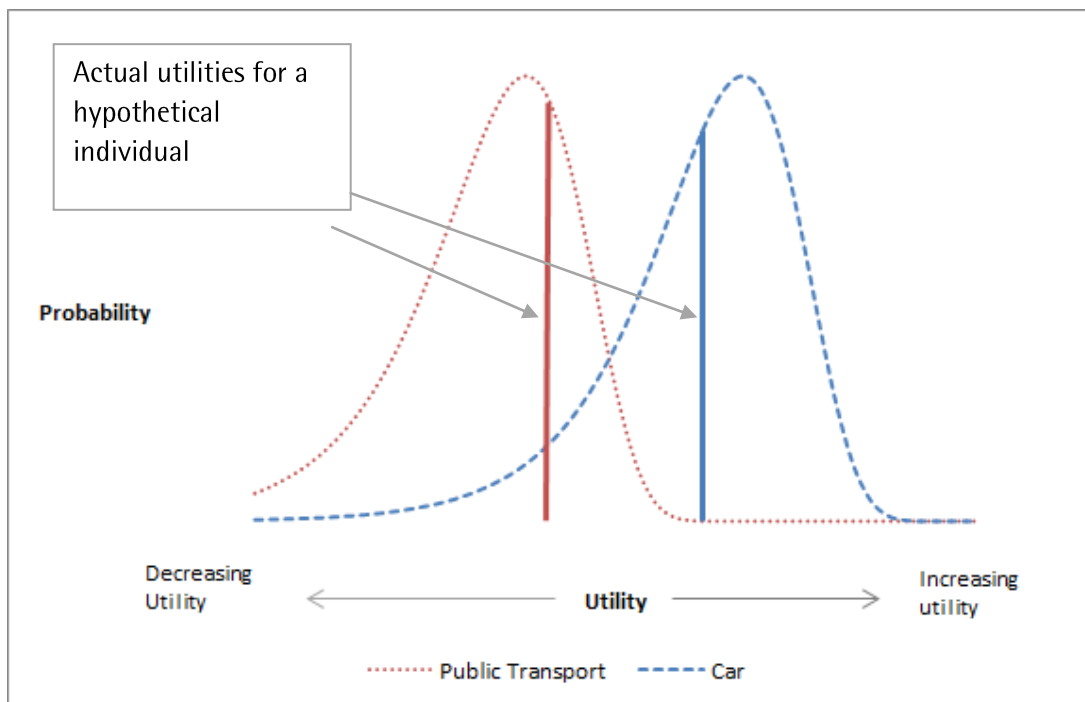
Figure 2 - Actual Utilities for a Hypothetical Person.

In contrast, Figure 3 presents another hypothetical individual; this time a person who chooses public transport. This individual sits far to the left on the car probability distribution – perhaps they don't have access to a car because their partner took the car to work, and so their only car option is to take a taxi. Whatever the reason, their public transport utility (the solid red line) is to the right of their car utility, so they choose public transport.
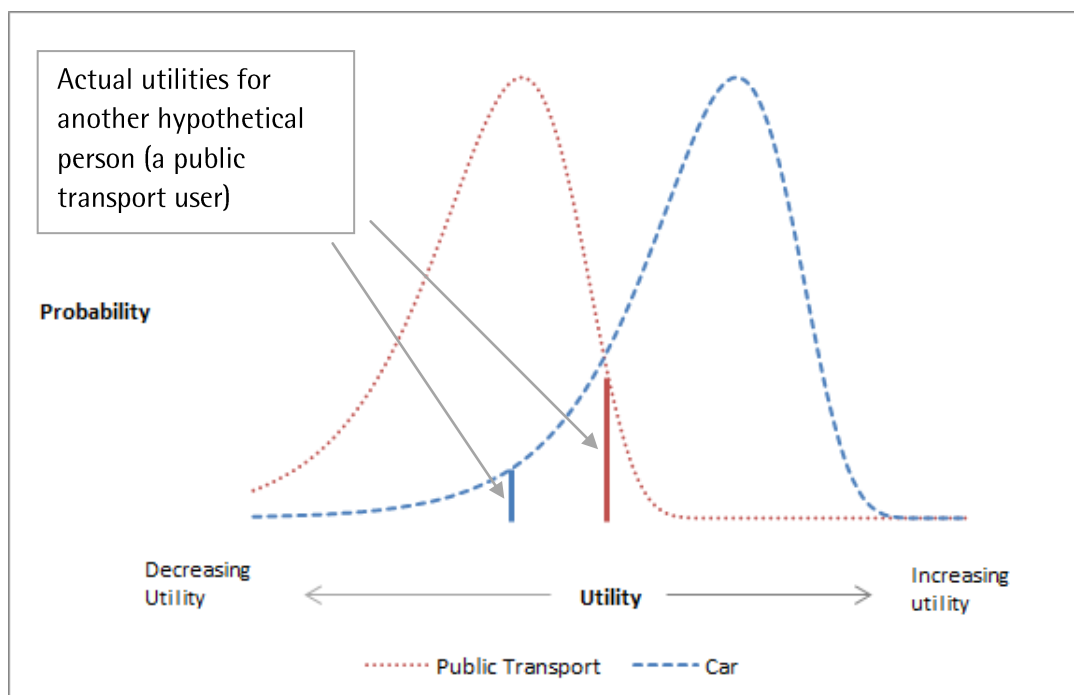

Figure 3 - Actual Utilities for Another Hypothetical Person (who chooses public transport)

This person is a rarity, however. By definition, people are most likely to fall near the centre of the two probability distributions. This is illustrated in Figure 4 below, which illustrates that the majority of people have a utility near the centre of our probability distributions. In this example, most people have a car utility greater than their public transport utility (95% of people, in fact).
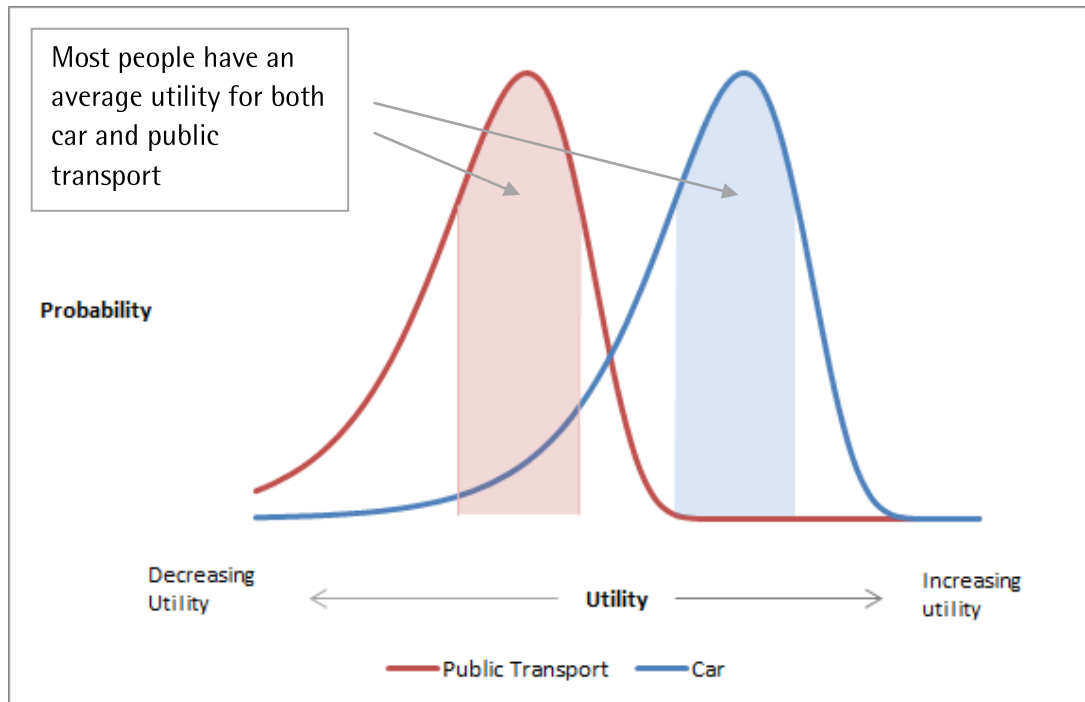
Figure 4 - People Commonly Reside at the Centre of the Distributions

Within this framework, scenarios, such as changes in travel time, policy variables, etc, can be viewed as shifts in the utility for one or more modes. For example in Figure 5 below we show a leftward shift in the utility for car travel. A decrease in utility is equivalent to an increase in cost, so this scenario might represent an increase in fuel costs or parking costs. Because the cost applies to all car travellers, the entire probability distribution moves left. In the example, our first hypothetical individual (the car user), has now switched to public transport; note that the car utility for our individual has shifted to the left of their public transport utility.

A reduction in car utility caused by an increase in car costs
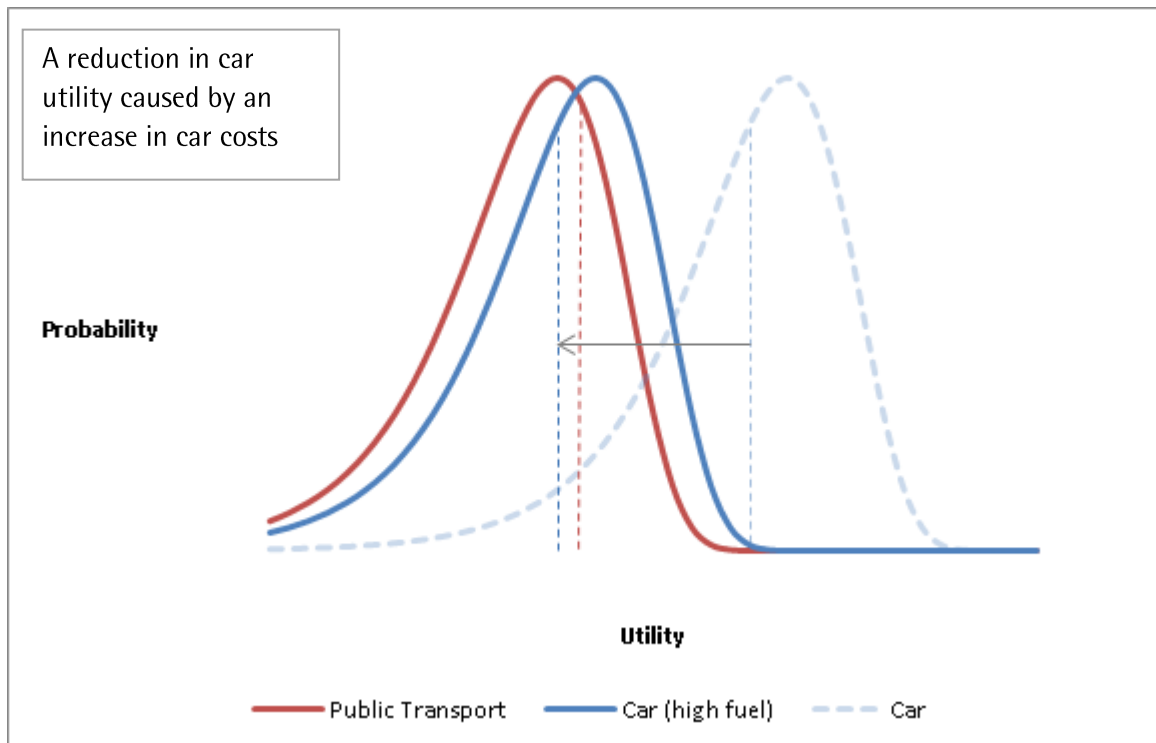
Figure 5 - A Shift in the Utility for Car

It should be evident that by moving the distribution of car utilities left or right, we will observe a change in the proportion of individuals who choose car and public transport. The proportion is often illustrated on a graph where the x-axis is the *difference* in utility between two alternatives, as in Figure 6 below.
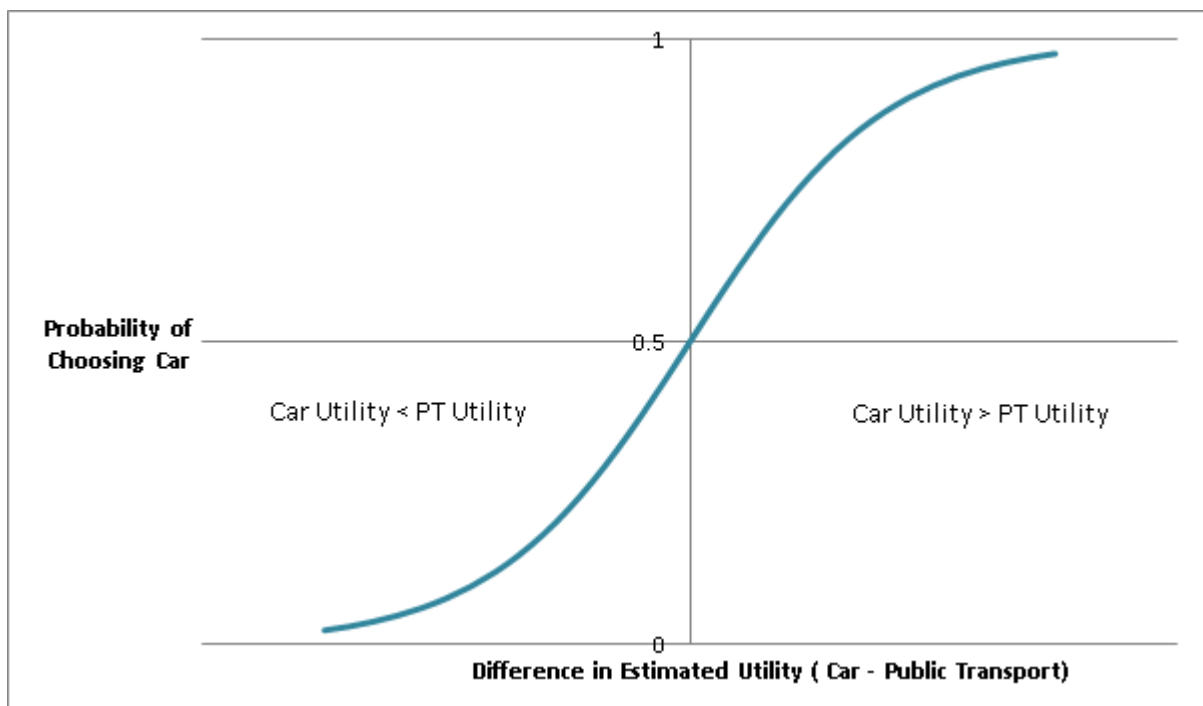

Figure 6 - Probability of Choosing Car Given Differences in Estimated Utility

Estimating *V*

Recall that our probability distribution for utility is comprised of two parts: *V*, which is our best estimate of utility (and which determines the centre of the probability distribution), and the random element ε which gives the probability distribution its *distribution*.

For our model to be accurate and useful, the estimated utility, *V*, should depend on variables such as travel time, fuel price, fares, etc. Then, by changing these variables, we can predict changes in mode shares.

For example, for car travel, we might assume that the key factors affecting utility are travel time, cost of fuel, cost of parking, cost of tolls, and car availability. In this case, our estimate of utility, *V*, would be defined as follows:

$$V = \beta_1 TT + \beta_2 FUEL + \beta_3 TOLL + \beta_4 PARKING + \beta_5 CARAVAILABLE$$

where the β s are parameters which capture the effect of each variable on our estimate of utility, and TT, FUEL, TOLL, PARKING and CARAVAILABLE are our x's, our known attributes of the car trip.

If a factor does not affect the utility of a car trip (for example, if we were to include an irrelevant factor such as the first digit of the licence plate), then the parameter for that factor (the β) should be zero.

By varying the values of travel time, toll, parking and car availability, we change our estimate of *V*, and thus change our predicted mode share. The β s determine how sensitive *V* is to changes in each variable.

Much of the remainder of this document will be dedicated to determining these β s based on the 22,000 people who filled out VISTA07 survey forms, and the choices that they made during their travel day.

Estimating ε

The random error term, ε, plays an *extremely* crucial role in our prediction of mode shares.

Consider the examples in Figure 7 and Figure 8 below.
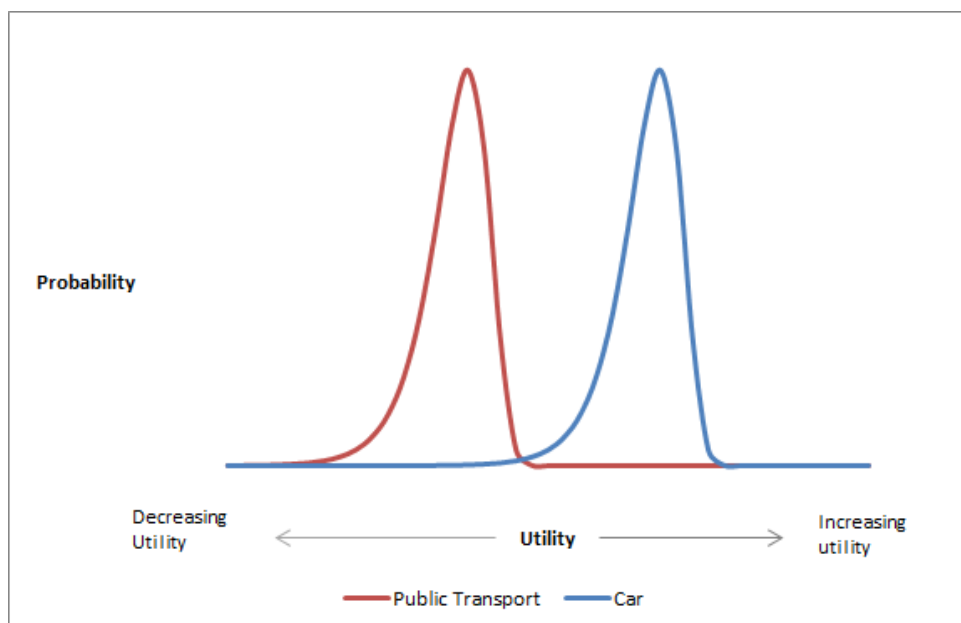
Figure 7 - A Small Random Error Term
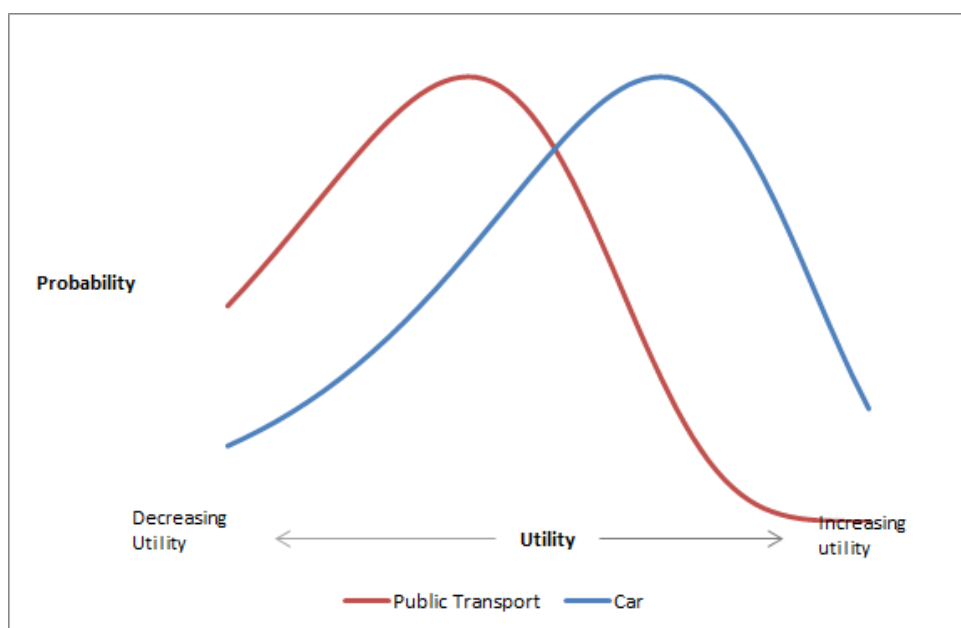
Figure 8 - A Large Random Error Term

In the first case, the random error term is small. As a result, the car and public transport probability distributions are quite separate, and we would thus predict that almost all people will have a higher utility for car than for public transport.

In the second case, the random error term is large, and as a result, there is considerable overlap in the probability distributions. In this case, there will be many more people who have a higher utility for public transport than for car. The predicted mode share will be closer to three quarters car.

Now, note that the mid-point of the distributions were identical in both examples. In other words, our estimates of utility were identical; all that varied was the scale of the random error term, and yet our predicted mode share went from close to 100% to close to 75%.

The scale of the random error term also dictates the sensitivity of the predicted mode shares. In the first example (small random error) the mode share will be insensitive to a small change in the car or public transport utilities. However, if the car utility were to move far enough left, and even just past the public transport distribution, then suddenly the mode share could flip from 100% car to 100% public transport.

By contrast, the changes in the second example will be much more gradual.

Conceptually, the random error represents all of the things which we don't know about the individual and the choices they face. If V is the embodiment of what we do know, then ε is the embodiment of what we don't know.

The more that we know, the more confident are our predictions. We predict with a probability close to 1.0 that an individual will choose a certain alternative.

The less we know, the less confident our predictions become, and the more likely our predictions are to hover near the mean mode share for the entire population. For example, a very poor model might predict an average public transport mode share of 14% for all Home Based Work trips, irrespective of the origin and destination.

So clearly it is important to know how much we don't know.

Along with estimating the β s, we will also estimate the scale of ε, again based on the travel decisions made by our 22,000 VISTA07 respondents. However, you won't see a value for ε reported in this document.

The reason is slightly involved, but fundamentally comes down to this.

Say we estimate all the β s, and the scale of ε. It so happens that if I then double all the β s, and also double ε then I arrive at a model with different parameters, but which produces *exactly* the same predictions of mode shares. Plotted, the relativity between the probability distributions would be identical – you couldn't tell one model from another. As such, the value for ε is only meaningful in a relative sense - relative to the units of the β s – and vice versa. Given this, we will set ε equal to 1.0, and calculate our β s relative to this. Therefore, the scale of ε is actually implicit in our β s. This is common practice.

There is one small catch, however, and that is that ε is not held constant across all alternatives. Rather, it is fixed for groups of alternatives, which we call nests. The relativities in the scale of ε between these groups will be important. We discuss this further in the following section.

3.1.2   The Nested Logit Model

In a standard logit model (as per the previous section), the distribution of the random error term, ε, must be identical across all alternatives. Referring back to Figure 7 and Figure 8 in the previous section, note how the spread of the distributions was always identical for both car and public transport.

We also implicitly made one other assumption in the previous section. Recall that each and every individual in the real world falls somewhere on our probability distributions for the utility of car and public transport. They generally fall near the centre of our distributions. Now, we made the assumption that these two distributions are unrelated, or *independent*; that is, one's car utility doesn't affect one's public transport utility, and vice versa.

Both these assumptions can break down in the real world.

Some alternatives (or modes, in our case), have an inherently greater or lesser amount which is *unknown* about them (remembering that the scale of the random error term is reflective of the scale of unknown factors).

The amount that we don't know about one's utility for cycling may differ from what we don't know about one's utility for car travel, or public transport. As such, the first assumption breaks down.

Furthermore, the utilities of competing alternatives are not always independent, especially when alternatives are very similar, or have a great deal in common. A common thought experiment highlights the choice between *red and blue busses.* Generally speaking, people don't have a great preference for red or blue busses; they care more about other things like travel time, reliability, etc. So, all other things being equal, if someone likes a red bus, they'll also like an equivalent blue bus. If they don't like a red bus, they won't like a blue bus. Clearly their preferences are linked – they are not independent – which would be a clear violation of our assumption about independence, if we were to include red and blue busses as separate alternative modes in our model.

We won't go into the detail, but violations of this kind can cause significant error in our predicted mode shares.

Nested logit models allow us to loosen these assumptions, which can improve our model's predictions.

The basic idea is that we group together similar alternatives (think red bus / blue bus) into what we call nests. A trip maker first chooses amongst nests, and then, having chosen a nest, then chooses amongst the alternatives which are grouped into that nest.

Nests can also contain nests, which lead to something of a tree-like structure. The structure we have adopted for the modelling of Home Based Work trips can be found in the next section, in Figure 9. We have grouped walk and cycle together, and called their nest "Non Mechanised". In terms of public transport, we have grouped walk access and car access to the transit system together into a nest called "Public Transport". However, walk and car access are themselves nests, each consisting of rail, bus and tram alternatives. This is discussed in more detail in the next section.

3.2   Mode Choice Structure

The nesting structure employed by the recalibrated Zenith model is presented in Figure 9 below. The blue rectangles represent the set of (mutually exclusive) alternative travel modes which are available to each trip maker. Alternatives are then grouped into nests, and nests of nests, which are represented by the green rectangles.
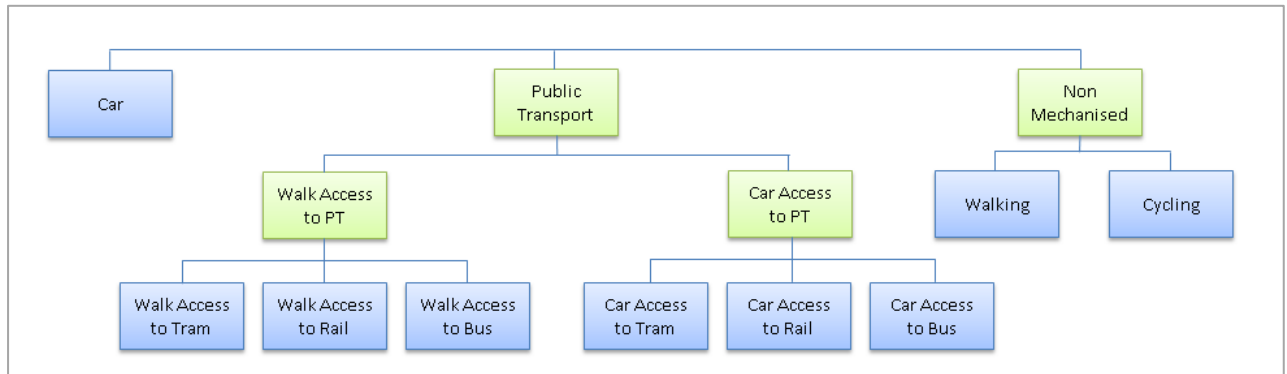

Figure 9 - Nesting of Modal Alternatives

This is quite a departure from the original Zenith model. The key differences are:

- Cycling has been included,
- Public transport sub-modes (tram, rail and bus) have been included at the bottom level.

The inclusion of public transport sub-modes in the Mode Choice model has been motivated by the desire to statistically estimate mode specific in-vehicle time weights, access penalties and transfer penalties using the VISTA07 survey. In the past, these key model parameters have been tuned to enable the model to match observed public transport demands, but have had little statistical or theoretical justification other than benchmarking against international standards.

This improvement is seen as a significant step forward for the Zenith model, in terms of functionality, transparency and justification.

It should also be noted that when choosing among the three public transport sub-modes, the trip maker is actually choosing which sub-mode to board first. This acts as no limitation on which modes can be used later in the journey. So, a "walk to bus" trip may involve a later interchange to rail or tram.

An alternative approach may have been to allow the trip maker to choose a "primary" public transport mode for the journey. If rail was considered more primary than bus, then a bus-rail trip would be expressed as a rail trip. Because a great many bus routes act as rail feeders, the role of bus would be two-fold: as a primary mode, and as alternative access mode to rail (car / walk / bus). While this has some elegance, it poses some challenges in software implementation, and for this reason we have opted against it, for now at least.

3.3   Inclusion of Mode Choice in the Overall Model Structure

The Zenith model includes the choice of mode after the choice of destination and departure time.

The ordering of the three key choices (destination, departure time, and mode choice) is a matter of some conjecture in the industry, with some models placing the choice of mode before destination, and others performing them simultaneously, with trip makers choosing from a sea of alternative mode / destination pairs.

The ordering is a matter of some importance, as it directly determines the relative sensitivity of each choice to changes in model inputs.

For example, take an individual living in South Yarra and working in the city, and who currently takes the train to work during the morning peak. If Zone 1 fares were increased by 50% during the peak, the challenge of the model is to determine whether the trip maker:

- Continues to take the train during the peak,
- Continues to take the train but travels earlier or later to avoid the higher fare,
- Switches to tram,
- Switches to car,
- Switches to walking,
- Switches to cycling,
- Quits their job and finds another one in a different location.

Of these alternatives, I would postulate that a change in destination is least likely. This is equivalent to saying that the choice of destination is relatively *insensitive*, and thus should be placed first, before choice of mode and departure time, at least for Home Based Work[1].

I would argue that the same applies to Home Based Education trips; that the choice of education location is primarily related to preferences towards individual schools, with the choice of mode a secondary constraint. But this no doubt varies within the population, depending on the importance placed by parents on the education of their children.

Given the key role that Home Based Work and Home Based Education trips play in public transport demands (which is a major focus of the Zenith model), we feel justified in placing destination choice before mode choice (at least in a hand waving sense).

However, we do think that a review of the ordering would be useful at a later date, if only to provide additional justification. We do expect, however, that for some trip purposes, destination choice will be more sensitive than mode choice, placing it later in the decision tree.

Take, for example, a respected transport planner, who drops in at the local bottle shop to grab a bottle of wine on the way home from work (by car). If a major residential development were built next door

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[1] While switching jobs as a result of changes in travel costs may seem extreme, we must note that the model is simulating long run equilibrium conditions. In the long run, higher peak zone 1 fares may alter house purchasing and labour market decision making, resulting in greater long run sensitivity in the choice of destination.

to the bottle shop, resulting in a parking shortage, the challenge for the model is to determine whether our skilled planner would:

- Continue to drop in at the bottle shop, even if it means spending some time looking for a park,
- Leave work early to get to the bottle shop while parking was still available,
- Walk or take public transport home, allowing him to reach the bottle shop without parking (bearing in mind it is a 15 minute drive from work to home),
- Drop in at a different bottle shop,
- Start buying in bulk to avoid having to stop there often,
- Stop buying wine all together (ha!).

In this case, a switch of destination (dropping in at a different bottle shop) is the most likely change (apart from maybe buying in bulk...), with no shortage of bottle shops to choose from. A switch in mode is most unlikely.

 As such, we believe that for Work Based Shopping trips (and probably shopping trips in general), the choice of destination is the most sensitive of all the choices, and could be placed after the choice of departure time and mode.

In the long term we envisage a "horses for courses" approach, where the ordering can vary by trip purpose. For now, however, we will continue to place destination choice before mode choice.

3.4 Modal Attributes

The following modal attributes have been included in the Zenith Mode Choice model:

Car

- Travel time
- Cost of fuel
- Cost of tolls
- Destination indicator [CBDCore, CBDNonCore, CBDFrame, OuterFrame] eg. parking costs

Walking
- Walking time

Cycling
- Cycling time

Public transport

- Walking time (access, egress and transfer combined)
- Car time (access or egress)
- Waiting time
- Tram in-vehicle time
- Train in-vehicle time
- Bus   in-vehicle time
- Number of transfers
   - tram – tram
   - tram – train
   - tram – bus
   - train – train
   - train – bus
   - bus – bus
- Fare
- Train station (off street) parking supply (applies to car access to rail only)

The values of these modal attributes vary by origin / destination pair, and by time of day. All have been sourced directly from the current Zenith model.

All costs have been expressed in 2008 Australian Cents. All travel times have been expressed in minutes.

Note that parking costs have not been explicitly included at this stage, but are instead represented by spatial constants. This decision, and other key assumptions are now discussed in more detail.

Also note that public transport crowding costs have not been included. We hope to include crowding at a later date.

3.4.1   Car Attributes

3.4.1.1   Car Travel Time

Car travel times have been sourced from a 2008 Zenith model run. Travel times vary by time of day, reflecting variations in traffic congestion. The Zenith model employs two generalised speed flow curves, which apply to freeways and non-freeways, as seen in Figure 10 below.
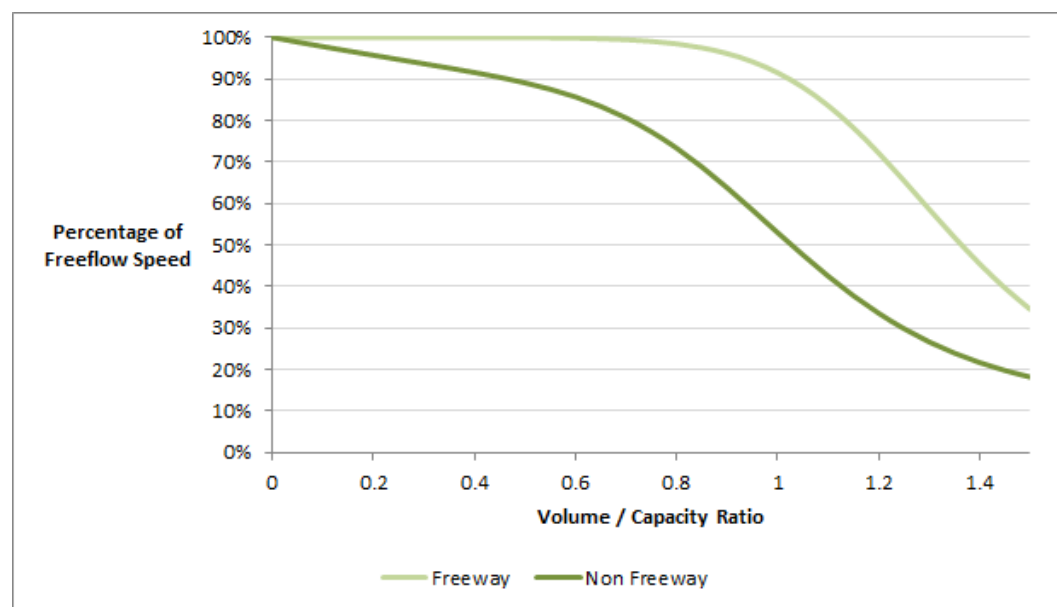
Figure 10 - Zenith Speed / Flow Curves

Each road link is assigned a free-flow speed and an hourly vehicle capacity. The ratio of demand to capacity (the Volume / Capacity ratio) is input to the relevant speed-flow curve above, with the resulting percentage multiplied by the free-flow speed to determine a congested speed.

3.4.1.2   Cost of Fuel

Fuel consumption has been calculated on a link by link basis using the fuel consumption curve presented in Figure 11 and defined in Equation 1 below.
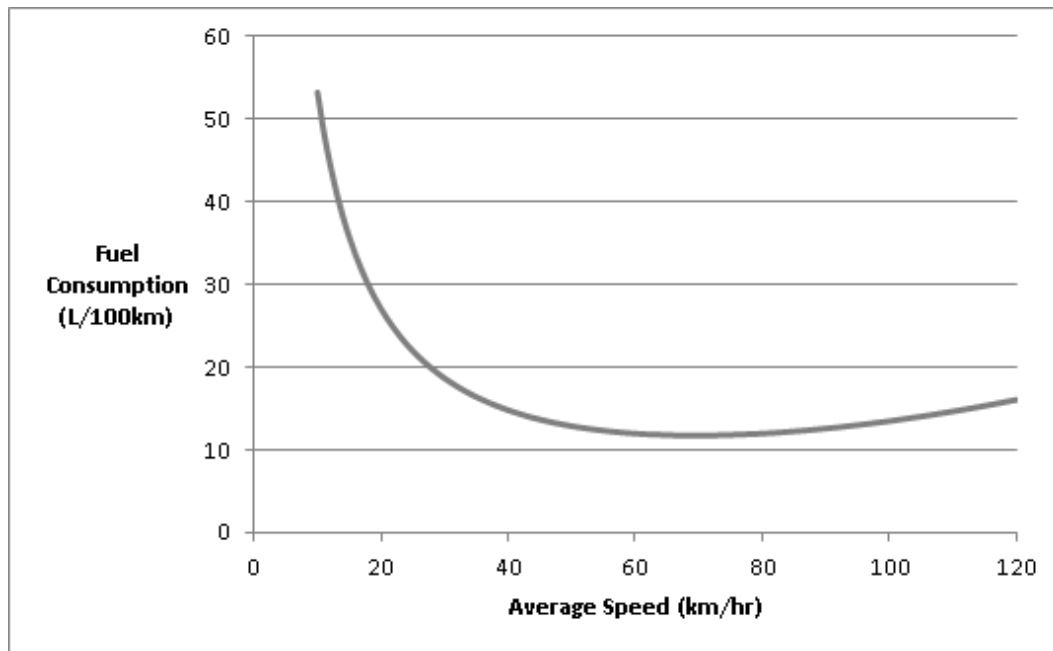
Figure 11 - Fuel Consumption Curve

$$F = \alpha + \frac{\beta_0}{SPEED} + \beta_1 SPEED + \beta_2 SPEED^2 \qquad (1)$$

Where *F* is the average fuel consumed per 100 km (in Litres), *SPEED* is the average travel speed on the link, in km/hr, and the α and β s are defined in Table 1 below.

Parameter	Value
α	0.361
β_0	528
β_1	0
β_2	0.000785

Table 1 - Fuel Consumption Parameters

Having calculated the link by link fuel consumption, the fuel consumption for each origin / destination pair was calculated based on the path a with least travel time. Given that travel speeds vary by time of day, fuel consumption also varies by time of day.

The cost of fuel was then calculated by multiplying the fuel consumption by the fuel price. A review of historical fuel prices highlighted considerable variation in price during the VISTA07 survey period. Given this, month by month average prices were included, allowing the fuel price to vary across survey

respondents. Fuel prices were only examined for Metropolitan Melbourne. The month by month average prices are presented in Table 2 below.

Month	Average Fuel Price (Cents)
April 07	125.7
May 07	130.4
June 07	129.5
July 07	126.8
August 07	121.6
September 07	122.5
October 07	125.6
November 07	133.2
December 07	139.0
January 08	140.4
February 08	137.0
March 08	140.1
April 08	144.0
May 08	145.3
June 08	160.7

Table 2 - Average Monthly Fuel Prices (Source: FuelTrac Website[2])

3.4.1.3   Cost of Tolls

For the purposes of recalibration, tolls have been set to their 2008 values (also in 2008 cents).

We have also removed the EastLink toll road, as it first opened on the 29th of June, 2008, and was first tolled on the 27th of July, 2008. This is outside the period of the VISTA07 survey.

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[2] http://www.aaa.asn.au/issues/petrol.htm

3.4.1.4   Destination Indicators (eg. parking costs)

Parking costs have a profound influence on the cost of travel by car to certain parts of Melbourne. Generally speaking, the cost of parking is highest in the central city, but significant parking costs are still observed in the areas near the CBD.

An initial review of parking costs (for commercial, off street parking) found that while reasonable information was available for the central city, there was very little information about parking in the broader CBD Frame.

It was also our view that a lack of parking supply could also add significantly to the perceived cost of parking, particularly in the inner suburbs.

Given our lack of information at the current time regarding parking costs and parking supplies, an alternative approach was adopted, whereby no parking charge was specified, but instead, we allowed the VISTA07 survey to tell us what level of parking charge would best explain the behaviour of the survey respondents.

To do this, inner Melbourne was divided into four regions:
- The CBD (Core), covering the CBD grid,
- The CBD (NonCore), covering Southbank, Docklands and parts of St Kilda Rd,
- The CBD Frame, extending into the very inner suburbs in the east, north and south,
- The Outer Frame, which extends into the inner eastern suburbs in the Yarra and Stonnington LGAs.

Two additional areas were also defined:
- Melbourne University
- Large Non-CBD Universities (Monash and LaTrobe)

These areas are shown in Figure 12 below.

The derivation of these areas was mostly based on an inspection of employment densities. However, we also took account of discrepancies between VISTA07 and the current model's estimates of public transport mode share in the inner east, which could be explained in terms of parking costs / supply constraints.
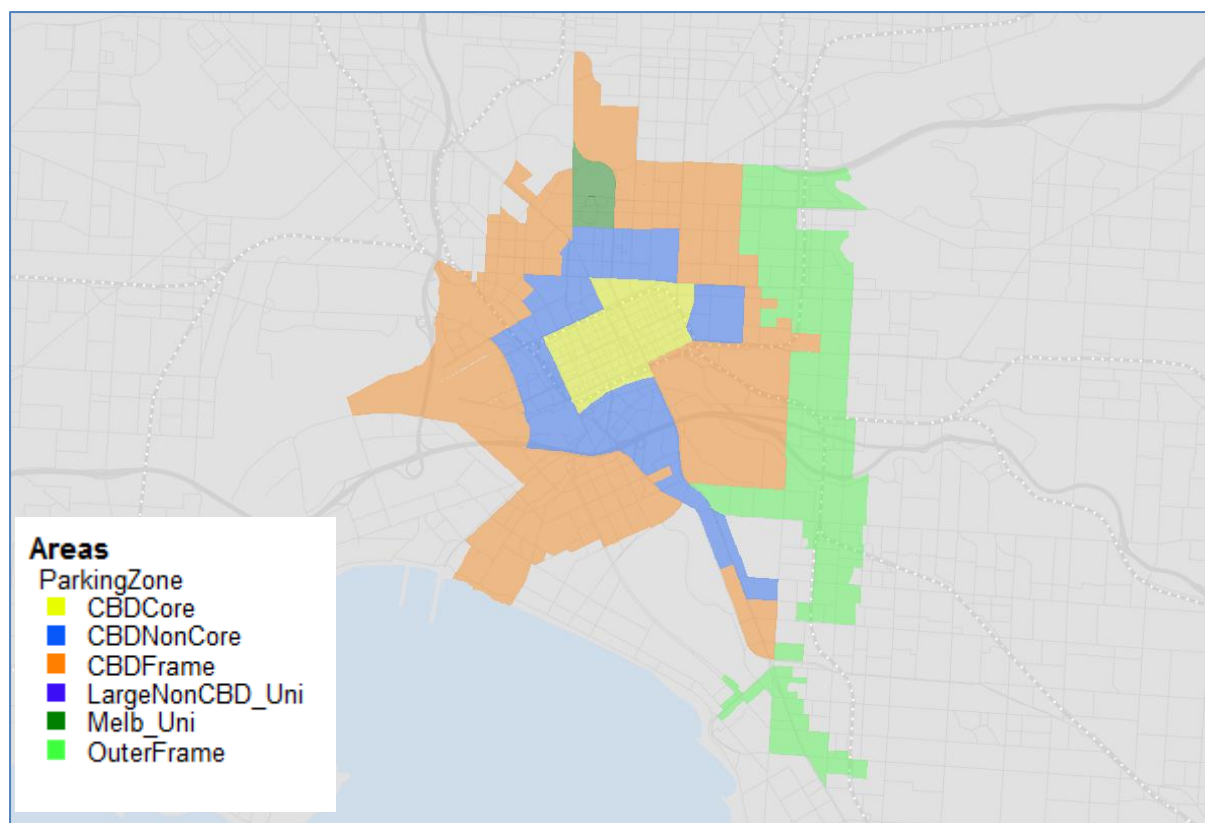
Figure 12 – Destination Indicator (Parking Charge) Areas

Figure 13 - Employment Density (ABS: 2006 Census Place of Work)

Each area was represented by an indicator (dummy) variable, taking a value of 1 if a trip was to the area, otherwise 0.

By converting the parameters to a monetary value, we can infer a total perceived cost of parking[3]. This cost includes the perceived cost of any monetary charges, as well as perceived costs associated with finding a park, as well as the perceived cost of walking between car park and destination.

By comparing these values to actual parking prices, we can explore perceptions relating to the indirect costs of parking.

In the near future we hope to extend this work to explicitly separate the direct and indirect costs of parking. To do this, however, we will need accurate information relating to parking costs and supplies (including on-street and private parking in areas outside the CBD). This approach will have greater explanatory power, and allow testing of policies around parking both costs and supply. It should also give us a better of idea of how parking will influence travel behaviour in the future.

3.4.2   Walking Attributes

Travel time is the only attribute assumed to affect the utility of a walking trip.

An average walking speed of 5km/hr has been assumed in the model.

3.4.3   Cycling Attributes

As with walking, travel time is the only attribute assumed to affect the utility of cycling.

As cycling has not previously been included in the Zenith model, we do not yet have a "cycling network" coded. Rather, we have assumed that the cycling network is identical to the pedestrian network, albeit with a higher average speed of 15 km/hr.

3.4.4   Public Transport Attributes

3.4.4.1   Travel times

All of the various travel time components (walking, car, waiting, tram, train and bus) have been sourced from a current Zenith 2008 model run.

The Zenith base year public transport network was updated to typical 2009 school term conditions using information supplied by Metlink on 4 December 2009. This information included revised train, tram and bus routes and stop locations, route extensions and frequencies

Where practical, stops have been coded at their actual locations. The key exception is stops located at either side of an intersection, which are typically grouped at the intersection.

Walking time is based on an average speed of 5km/hr, while car travel time is based on the congested road speeds output from a Zenith traffic assignment (which vary by time of day).

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[3] Strictly, the resulting parameters represent an all encompassing disutility of travelling to each area by car, resulting from all unobserved factors (not just parking). However, we believe it safe to assume that parking is the key driver of these parameters.

Waiting times are currently based on "half the headway", where the headway is based on the combined frequency of "sensible" services[4]. We intend to review this in the future.

In-vehicle times for rail are based on the timetable, while in-vehicle times for on-road trams and busses are based on the congested road speeds output from a Zenith traffic assignment. Where trams and busses have their own right of way, timetable information has generally been used.

3.4.4.2 Transfers

The number of transfers required to make the trip between origin and destination by public transport has been taken from the Zenith 2008 model run. Transfers have been separately identified for each pair of transit modes.

3.4.4.3 Fares

The fares in the Zenith model have been updated to current conditions, and then discounted to 2008 cents.

The definition of fares is complicated by the range of ticket types available. As such, due to the lack of information currently available to VLC, a number of heroic assumptions have been made to formulate a single average fare, for travel between each pair of fare zones.

The current fare prices in Metropolitan Melbourne are:

Value MetCards	Zone 1		Zone 2		Zone 1 + 2	
	Full	Concession	Full	Concession	Full	Concession
10x2hr	$ 29.40	$ 14.70	$20.20	$ 10.10	$ 49.60	$ 24.80
10x city saver						
5 x daily	$ 29.40	$ 14.70	$20.20	$ 10.10	$ 49.60	$ 24.80
5 x daily senior						$ 16.50
2hr	$ 3.70	$ 2.30	$ 2.80	$ 1.70	$ 5.80	$ 3.30
Daily	$ 6.80	$ 3.70	$ 4.80	$ 2.70	$ 10.60	$ 5.60
weekly	$ 29.40	$ 14.70	$20.20	$ 10.10	$ 49.60	$ 24.80
Monthly	$109.60	$ 54.80	$73.40	$ 36.70	$ 169.00	$ 84.50

Table 3 - Metropolitan Fares

All fares effective from 1 January 2011
Source: htps://store.metlinkmelbourne.com.au/index.php

These assumptions include:

- The Ratio of User Types [Full Fare : Concession] = [2:1]
- The breakdown of ticket types is:
  - 10x2hr   20%
  - 10x city saver   -
  - 5 x daily   20%

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[4] A sensible service is one that provides a viable alternative for reaching the destination

- 5 x daily senior -
- 2hr   10%
- Daily   10%
- Weekly   20%
- Monthly   20%
- The number of one-way trips made per ticket is:
  - 10x2hr   10
  - 10x city saver   –
  - 5 x daily   10
  - 5 x daily senior -
  - 2hr   1
  - Daily   2
  - Weekly   10
  - Monthly   41.6
- A discount of 5.2% between 2011 and 2008.

Given these assumptions, a zone to zone one-way fare price (in 2008 dollars) was calculated. The fares are presented in Table 4 below.

Fare Zone	Zone 1	Zone 2
Zone 1	$ 2.39	$ 3.89
Zone 2	$ 3.89	$ 1.66

Table 4 - Metropolitan Fare Table

* NOTE: No allowance has (yet) been made for the overlap in the Zone 1 & 2 fare boundaries.

A thorough review of Regional fares is yet to be conducted.

3.4.4.4   Train Station Off Street Parking

Train station parking supplies were initially sourced from the Melway 2008. Later, it was discovered that the Metlink website also reports parking by station, and some cross checking was performed to confirm their consistency. They were found to be broadly consistent.

To further explore the quality of the data, we compared the parking supply with the results of the Metlink Rail OD survey (2009) which, among other things, reports an estimate of the number of rail passengers who park at the station. This comparison is presented in Figure 14 below.
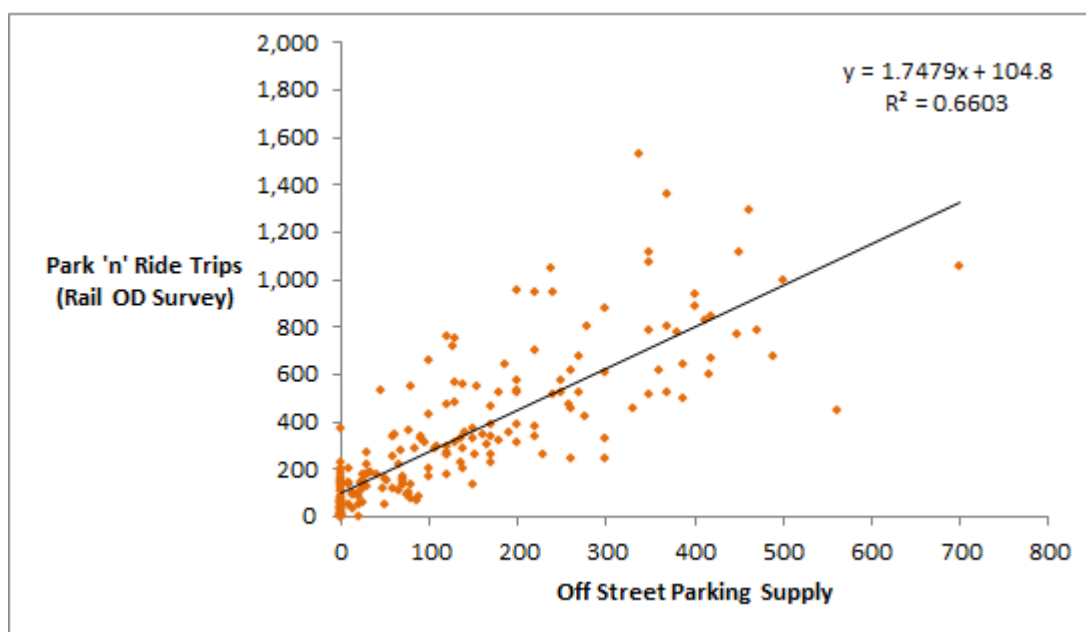
$$y = 1.7479x + 104.8$$
$$R^2 = 0.6603$$

Figure 14 - A Comparison of Train Station Off Street Parking and Estimated Park 'n' Ride trips

It is evident that the number of park 'n' ride trips is significantly greater than the parking supply, with a gradient of 1.75, and a y-intercept of 105 for the line of best fit. This might indicate that some car parks are being used more than once a day, though this is thought to be reasonably unlikely given that park 'n' ride trips generally involve a high duration activity such as work. It seems more likely that on-street parking is also serving park 'n' ride trips.

Nonetheless, there is good correlation between off-street parking supply and the estimated number of park 'n' ride trips, which suggests that off-street parking supply will play an important explanatory role in the utility for car access trips.

3.5 Socio-Demographic Characteristics

Only one socio-demographic attribute has been included in the Mode Choice model: household car ownership. Our past experience is that car ownership plays a fundamental role in modal choice decisions.

However, we are deriving separate mode choice models by trip purpose, and each trip purpose is characterised by a particular demographic profile. In this limited sense, socio-demographic factors are taken into account.

In future, we would prefer to move to a disaggregate model which would allow the inclusion of socio-demographic variables such as income, occupation, gender, age, licence holding, etc.

4 Model Estimation

In this Section we present the results of our statistical estimation of model parameters.

In a few selected cases, we have opted to override certain estimated parameters, where we feel that the statistically estimated parameter is not suitable. Unsuitable parameters can result from a lack of sample in VISTA07, inaccuracies in VISTA07 data, inaccuracies in our construction of the travel alternatives available to trip makers, or from problems with the structure of the model.

The adopted model parameters are contained in Section 5.

4.1 Home Based Work

4.1.1 Profile of Demand

In the context of mode choice, Home Based Work (HBW) trips are of critical importance.

Based on VISTA07, HBW trips are responsible for:

- 26% of *daily* car driver trips
- 39% of *peak* car driver trips.
- 39% of *daily* road network distance
- 58% of *peak* road network distance

The role of HBW trips in public transport demands is even greater:

- 37% of *daily* public transport trips
- 46% of *daily* public transport passenger kilometres
- 56% of *peak* public transport trips
- 65% of *peak* public transport passenger kilometres

Clearly, changes in mode choice for HBW trips will have a significant impact on both road and public transport demands, particularly in the peak.

4.1.2   Model Estimation

A nested logit model has been estimated for HBW, based on the travel made by VISTA07 respondents. The parameters to the model are presented in Table 5 below. The parameters are organised into three groups:

- Betas – which are the coefficients of the variables in the model,
- Constants – which are alternative specific constants for the various modal alternatives,
- Structure – which includes the scale parameter for each nest

The first column of numbers contains our estimated parameter values for each of the betas, constants and scales.

Given that we are working with a sample of HBW trips, our parameter estimates cannot be precise. If we were (hypothetically) able to take a series of samples, instead of just one, then our parameter estimate would vary between the samples, and would follow a normal distribution. Given our known sample size, and variation in the sample, we can estimate what the standard deviation of this normal distribution would be, and it is presented in the second column of numbers as the standard error.

Given that parameter estimates are not precise, there is a chance that irrelevant variables – variables which truly do not impact utility – can have parameter estimates that are non-zero. This could be the case with some of our variables; that their true value is zero, but our estimate is non-zero, due to our random sample. Given that we can estimate the distribution from which the parameter estimates are drawn (as in the previous paragraph), we can estimate the probability that our parameter estimate could occur, *given that the true value is, in fact, zero*. If this probability is small, then the true value of the parameter probably isn't zero after all. If the probability is high, then the true parameter value could very well be zero, or even of the opposite sign; it is generally advisable to remove such parameters. This probability is presented in the P-VALUE column, where 0.05 indicates a 5% probability. Generally speaking we like our p-values to be less than 0.05, but it is possible to include parameters with a p-value greater than 0.05 if the parameter estimate is of the correct sign and has an intuitive magnitude. Sensible judgement is required.

We will now explore what these parameters mean.

Parameters	Re-estimated		
	PARAMETER ESTIMATE	STANDARD ERROR	P-VALUE
BETAs			
Car			
Car travel time (mins)	-0.0578	0.0061	0.0000
Fuel cost (cents)	-0.0021	0.0009	0.0248
Fuel consumption (litres)	0.2886	0.1347	0.0321
Toll (cents)	-0.0009	0.0003	0.0007
Dest - CBD Core	-2.6081	0.0995	0.0000
Dest - CBD Frame	-1.5573	0.1164	0.0000
Dest - CBD NonCore	-1.9468	0.1142	0.0000
Dest - Outer Frame	-0.7710	0.1786	0.0000
0 car household	-4.4145	0.1931	0.0000
1 car household	-1.3584	0.0709	0.0000
Cycling			
Cycling time (mins)	-0.0675	0.0112	0.0000
Walking			
Walking time (mins)	-0.0937	0.0072	0.0000
Intrazonal walking time (mins)	-0.0240	0.0218	0.2697
Public Transport			
Walk access time (mins)	-0.1234	0.0080	0.0000
Car access time (mins)	-0.1585	0.0278	0.0000
Waiting time (mins)	-0.0150	0.0064	0.0188
Travel time - tram (mins)	-0.0740	0.0091	0.0000
Travel time - train (mins)	-0.0732	0.0108	0.0000
Travel time - bus (mins)	-0.0258	0.0099	0.0091
Fare	-0.0001	0.0008	0.8747
Transfers - Tram / Tram	-1.0510	0.2267	0.0000
Transfers - Tram / Train	-1.9133	0.1304	0.0000
Transfers - Tram / Bus	-2.0264	0.2006	0.0000
Transfers - Train / Train	-0.8069	0.1762	0.0000
Transfers - Train / Bus	-2.2995	0.1669	0.0000
Transfers - Bus / Bus	-1.3164	0.3806	0.0005
Smart Bus	0.5045	0.3528	0.1527
Regional Bus	-0.4631	0.3516	0.1877
Public Transport - Car Access			
0 car household	-5.4334	1.2040	0.0000
1 car household	-1.4442	0.3086	0.0000
Public Transport - Car Access to Rail			
Train Station Parking	0.0039	0.0007	0.0000
Constants			
Car			
Car	0.2177	0.1657	0.1888
Cycling			
Cycling	-3.1228	0.2206	0.0000
Public Transport			
Walk <=> bus	-2.8788	0.3283	0.0000
Walk <=> tram	-1.9748	0.3115	0.0000
Walk <=> train	-1.6451	0.3030	0.0000
Car <=> tram2	-9.3809	1.1934	0.0000
Car <=> bus	-10.1124	1.2251	0.0000
Car <=> train	-8.1133	1.1880	0.0000
Structure			
Scales			
Non Mechanised	0.9370	0.1115	0.0000
Public Transport	0.7200	0.0649	0.0000
Public Transport - walk access	0.7096	0.0564	0.0000
Public Transport - car access	0.4992	0.0606	0.0000

Table 5 - Model Parameters for HBW

4.1.2.1 Travel time parameters

The estimated travel time parameters are summarised in Table 6 below.

Travel Time Parameters	Re-estimated PARAMETER ESTIMATE	Ratio to Car Time
BETAs		
Car		
Car travel time (mins)	-0.0578	
Cycling		
Cycling time (mins)	-0.0675	1.17
Walking		
Walking time (mins)	-0.0937	1.62
Intrazonal walking time (mins)	-0.0240	0.42
Public Transport		
Walk access time (mins)	-0.1234	2.14
Car access time (mins)	-0.1585	2.74
Waiting time (mins)	-0.0150	0.26
Travel time - tram (mins)	-0.0740	1.28
Travel time - train (mins)	-0.0732	1.27
Travel time - bus (mins)	-0.0258	0.45

Table 6 - Travel Time Model Parameter for HBW

It is useful to express each parameter relative to some standard, and we have adopted car travel time as that standard. The ratio of each travel time parameter to car travel time is presented in the second column of numbers.

Cycling

It can be observed that cycling time has a ratio of 1.17 relative to car time. This value will be highly sensitive to our assumption for cycling speed (we have assumed 15km/hr). If we increase our cycling speed, then the parameter estimate will increase.

Walking

Walking time has a parameter of 1.62, though intrazonal walking time receives an *additional* 0.42. This indicates that people generally prefer time spent in a car to time walking. The value is in line with expectations – the current Zenith model uses a factor of 1.5. It is nice to have the VISTA07 survey confirm a factor which we have previously assumed without supporting evidence.

Walk Access to Transit

Walk access time has a higher factor 2.14, which applies to the access and egress legs, as well as transfer time between stops. It seems that people don't like long walks to / from / between public transport! We believe that this factor may be higher for walks between public transport stops, though have not tested this yet.

Car Access to Transit

Car access time has an even higher factor of 2.74. We believe this to be because of the extra cost involved in kiss 'n' ride trips. The car leg of a kiss 'n' ride journey is made by (at least) two people, so the time of at least two people is being consumed, which increases the "value" of this time. Furthermore, the driver in this situation either has to drive home afterwards, or go on to their own destination, in which case they will have made a detour of some kind to visit the train station.

Waiting Time

Waiting time, on the other hand, has an interestingly low factor of 0.26. Broadly, there three possible reasons for this:

1. People don't mind (or don't perceive) the time spent waiting for a public transport service (we doubt this)
2. The Zenith model is over-estimating the time that people spend waiting. For instance, if were to quarter all waiting times, the factor of 0.26 would quadruple to 1.06.
3. It is a mathematical artefact of an incorrectly specified model. More on this in a short while.

We believe that reason 2 is plausible, though reason 3 cannot be ruled out at this stage.

In terms of reason 2 – the over-estimation of waiting times – the Zenith model currently assumes that passengers wait for half of the average headway, given the combined frequency of sensible services at a stop. We think that in the case of HBW trips that this is an over-estimate. Commuters generally know the timetable, and to the extent that services are reliable, commuters can time their arrival at a stop to minimise their waiting time. For example, if a service runs every 20 minutes, then the model currently assumes that passengers will wait for 10 minutes, on average. In reality, the average commuter may time their trip to wait only 5 minutes.

Further to this, our average headways are based on average service frequencies across a time period. However, service frequencies are not constant over a period; service frequencies are highest at periods of high demand. Given this, the majority of commuters will experience a higher frequency (lower wait time) than indicated by the model.

We hope to analyse, and potentially improve the model's calculation of waiting times at a later stage.

In terms of reason 3 – suggesting that the model may be incorrectly specified – we believe that there is heterogeneity (mixed views) in the population regarding public transport as a mode, and towards busses in particular (which tend to have higher waiting times). This could cause a bias in certain parameter estimates.

Transit In-Vehicle Time

Travel time on trams and trains incurs a factor of 1.28 and 1.27 respectively, relative to car travel time. Bus, however, has a surprisingly low factor of 0.45. The factors for tram and train are quite intuitive; the factor for bus requires an explanation.

Once again, there are three possible explanations for the bus factor:

1. People don't mind the time spent on board busses (at least relative to car, train and tram),
2. The model is over-estimating bus travel times,
3. It is a mathematical artefact of an incorrectly specified model.

The reality may be a mixture of these reasons.

In terms of Reason 1, it is possible that in the peaks (which is when most commuting trips occur), the time spent on board busses is more pleasant than time spent on trams and trains, due to *crowding*. It is our (unjustified) theory that busses are less crowded in the peaks than trams and trains, which could help to explain this factor (I would appreciate some feedback on this view). We could test this theory by including crowding as a variable in the estimation process, and we hope to do this at a later date.

In terms of Reason 2, we have no evidence to support this at this stage, but hope to explore it in the near future.

In terms of Reason 3, we believe that the heterogeneity mentioned in the discussion of waiting times might be to blame. It is generally accepted that perceptions of bus are generally less favourable than those for tram and train, but there will be a mix of perceptions across the population.

There are two ways for negative perceptions of bus to manifest themselves in the model: as a constant (a higher penalty for bus travel), or as a higher factor on travel time. The estimation process is suggesting that the best way to explain the behaviour of commuters in the VISTA07 survey is through a high penalty, and a low factor on travel time.

We believe that this may be due to a split in perceptions. There are some people who routinely take the bus, and will have a good knowledge of the parts of the bus network relevant to them. These people are in a position to take account of bus travel times in their mode choice decisions. Then there are other people who will never take a bus in their lives, irrespective of its travel time. These people have a very high penalty for bus, have no knowledge of the timetable, and take little account of the bus travel time. They simply disregard bus an alternative. Such people may have a factor of zero for bus travel time.

We believe that this mix of views may be the cause of the low factor on bus in-vehicle time.

It is possible to build a model which explicitly accounts for this mix of views, and this is something that we hope to explore in the near future.

For now, we are undecided whether to leave the bus factor as it is, noting that the combination of penalty and travel time factor derived from the estimation process best explains the VISTA07 survey, or whether to adjust it to a more normal level. We will reserve judgement until the overall model validation process is underway.

4.1.2.2   Cost parameters

There are three cost variables included in the model:

- Fuel
- Fares
- Tolls

Parking costs have been represented by destination indicators for the reasons described in 3.4.1.4.

The estimated parameters for each cost attribute are presented in Table 7 below.

Cost Parameters			
	Re-estimated PARAMETER ESTIMATE	Implied $/hr	Implied min/$
BETAs			
Car			
Fuel cost (cents)	-0.0021	$16.5 / hr	3.65
Toll (cents)	-0.0009	$37.6 / hr	1.60
Public Transport			
Fare (cents)	-0.0001	$262.9 / hr	0.23

Table 7 - Cost Parameters for HBW (2008 AUD)

We will now discuss each parameter.

Fuel Costs

For each attribute we can calculate an implied value of time.

For example, the implied value of time for fuel is $16.5 / hr, which is calculated as follows:

$$Implied\ VOT(fuel) = \frac{\beta_{CarTime}}{\beta_{Fuel}} \times \frac{60}{100}$$

Inverted, this says that $1 of fuel is equivalent to 3.65 minutes.

The value of this parameter determines how fuel costs are integrated into an overall generalised cost in the model, and will dictate the sensitivity of the model to changes in fuel costs.

It should be noted that this implied value of time should not be interpreted as a true value of time estimate, though it is useful to compare it to traditional value of time measures.

Rather, the implied VOT indicates the degree to which fuel costs are *perceived* at the point of decision making. For example, some people will have an accurate idea of the fuel cost for their trip to work, and may rationally incorporate this cost into the mode choice decision. Other people may have little idea (or an inaccurate idea) of the fuel cost, while others may simply not even consciously or unconsciously think about it when making their decision (at least within some range of fuel prices). Others may have their fuel costs paid for them by an employer.

Given this mix of information and decision making processes, we arrive at an average implied value of time, which best explains the behaviour of the commuters in the VISTA07 survey.

It is worth stressing the point: the VISTA07 respondents appear to (on average) take some degree of fuel cost into account in making their mode choice decisions, and we can measure it! It's quite remarkable!

Comparing the implied VOT to a traditional VOT (say $12/hr), we could say that (on average), 72% of the fuel cost is taken into account in the mode choice decision of commuters.

One word of caution, however: this parameter has been derived as a result of changes in behaviour resulting from variations in fuel price over the period. As noted in Section 3.4.1.2, we have utilised the month by month average fuel price (for Metropolitan Melbourne) over the period of the VISTA07

survey to estimate the cost of fuel to each respondent. These changes in behaviour could be viewed as a short run response to spikes in fuel price. The long run effect on behaviour may be different, and we should keep this in mind when using this parameter to make long term predictions in response to significant changes in fuel price. We may over-estimate the long term sensitivity to fuel price.

We think it may, however, be possible to disentangle the short and long run effects of variations in fuel price by using time series household travel survey data, such as a pooled VISTA07 and VISTA09, or perhaps by using the Sydney Household Travel Survey, which has been collected annually for over a decade.

Toll Costs

The implied VOT for toll costs is considerably higher: $37.6 / hr, or 1.6 minutes per dollar, suggesting that commuters are relatively insensitive to tolls when making their mode choice decision. A $4 toll would only equate to 6.4 minutes of generalised time.

Compared with a traditional VOT of $12/hr, we can say that (on average) only 32% of the toll value is taken into account in the choice of mode. Interestingly, VLC already had a factor in the model with approximately this value (0.25, in fact). The inclusion of this factor was found to be necessary in order for the model to match counts on toll roads. It is nice to have the VISTA07 survey confirm what was previously an unjustified factor in the model.

We should not immediately jump to the conclusion that commuters disregard tolls when making their mode choice decision. Rather, we should review how the cost of tolls has been determined. The Zenith model has been used to estimate the toll paid on any journey (for all origin / destination pairs). We cannot use a value specified by the survey respondent, because we also need a toll value when the respondent chose another mode, such as public transport (irrespective of what mode was chosen, we need to reconstruct the attributes of all alternatives that were available, which means defining tolls for car trips that were never made by the respondent).

Now, in the current work, an "all-or-nothing" path has been used to generate an estimated toll. In other words, we have taken the toll from the path with least generalised cost. If, for example, the least cost path uses a part of CityLink, then the toll will be set accordingly, and this is the toll which is input into the estimation process.

In reality, however, those who are sensitive to the cost of toll can avoid CityLink, while still taking car. They simply take an untolled path. This is why only 32% of the toll is taken into account; because it is easily avoided by those who want to.

A better way of modelling this would be to divide the car mode into tolled and untolled alternatives. Respondents in VISTA07 were asked to provide a list of major roads used on the trip, and so it is possible (depending on the quality of this data), that we could indicate whether the user chose a tolled or untolled path. This would be a very elegant solution, and is something we would like to explore in the near future.

Fare

Somewhat disappointingly, the parameter on fare has come out very close to zero, resulting in an unrealistic implied value of time of $263. It is disappointing because we believe that fares do, in fact, play a role in the mode choice decision, and because we can't do sensitivity testing on fare prices if we don't have a parameter for fare.

During much of our work, fare did have a sensible parameter, but as later variables were added, fares lost its significance.

One difficulty we face is that fare is loosely correlated with in-vehicle travel time; however, with a zonal system there should be enough variation in the ratio of travel time to fare for us to be able to calibrate a parameter. Another difficulty is defining the fare itself. With a multitude of ticket types available (2 hour, daily, 5 x daily, weekly, monthly, etc), it is difficult to define a single fare value. The blend of ticket types will also vary by trip purpose. We are also yet to do a thorough review of the interregional fares, which is crucial as interregional tickets will provide variation in the payable fare, which will assist in the model estimation process.

Given these factors, we are hopeful that an intuitive parameter for fare is obtainable given more accurately defined fares.

We hope to rectify this in the near future. Asserting a parameter which achieves a sensible elasticity to fare prices is a very real possibility; the only complication is adjusting all the other parameters to support this.

4.1.2.3 Household car ownership

Household car ownership plays a very significant role in the mode choice decisions of commuters.

During our work it was found that 2 and 3 car households behave identically, but 0 and 1 car households are much less likely to travel to work by car. Given this, we used 2 and 3 car households as our benchmark, and calculated constants (penalties) which apply to 0 and 1 car households. Separate parameters were calculated for trips by car (as the primary mode), as well as for car access to transit.

The resulting model parameters are presented in Table 8 below.

Household Car Ownership Parameters	Re-estimated PARAMETER ESTIMATE	Equivalent Travel Time Penalty (minutes)
BETAs		
Car		
0 car household	-4.4145	76.4
1 car household	-1.3584	23.5
Public Transport - Car Access		
0 car household	-5.4334	94.0
1 car household	-1.4442	25.0

Table 8 - Household Car Ownership Parameters for HBW

Alongside each parameter we have included an equivalent travel time penalty. Owning no car acts as a 76 minute penalty on travelling by car, and a 94 minute penalty on making a car access to transit trip. The significant nature of these penalties is not surprising; it is hard to travel by car if you don't

own one (note, it is still possible to obtain a lift from someone else, presumably not from the same household).

Owning one car is still a significant, but lesser, impediment, with a penalty of 24 minutes for car trips, and 25 minutes for car access to transit. It is reassuring that these values are consistent.

4.1.2.4 Destination Indicators (parking costs)

As discussed in Section 3.4.1.4, constants (penalties) have been calculated for travel to certain destinations. We will cautiously interpret these penalties as the perceived cost of parking, and work towards developing a model that accounts for parking costs (early bird and hourly), and parking supplies (on street and off street), in calculating a perceived cost of parking. This work is only step one.

The destinations for which penalties have been calculated are represented in Figure 15 below.

The estimated model parameters, and equivalent penalties in minutes and dollars are also presented in Table 9 below.
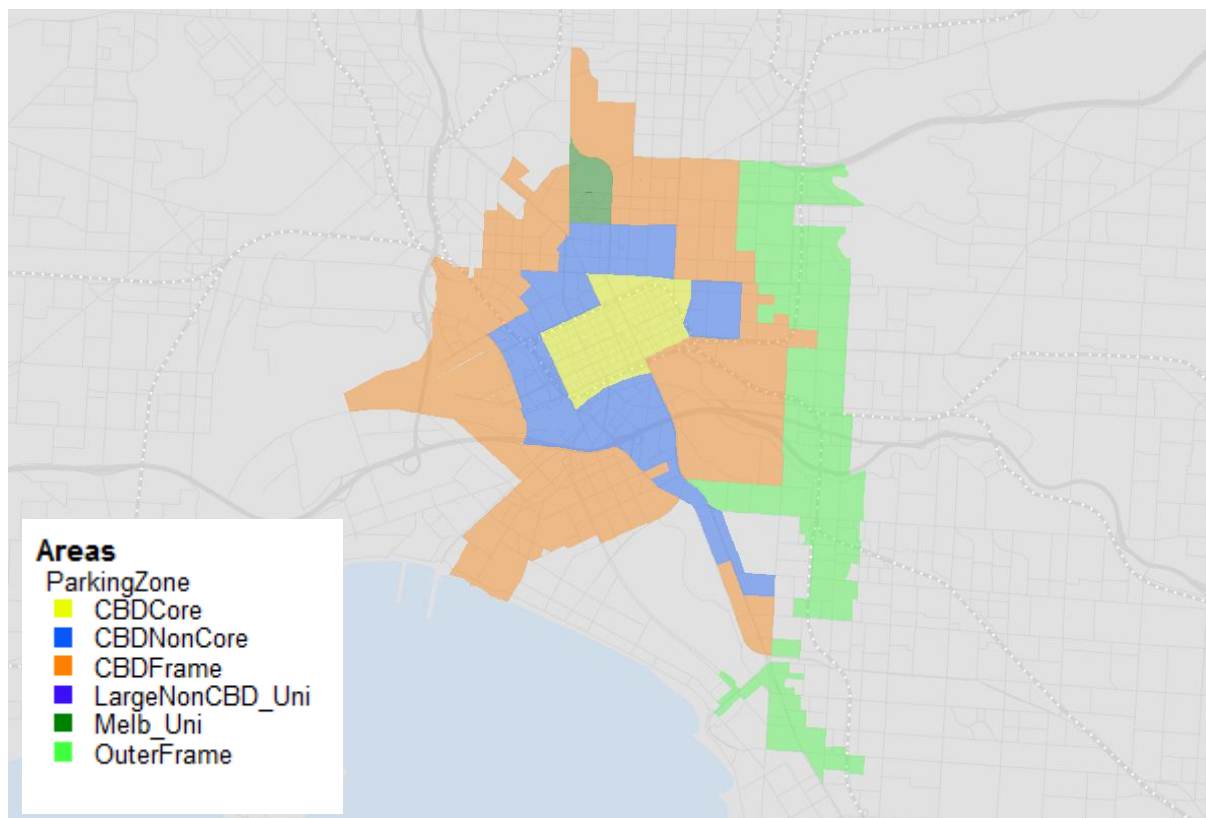

Figure 15 - Destination Indicator (Parking Charge) Areas

Destination Constants			
	Re-estimated		
	PARAMETER ESTIMATE	Equivalent Travel Time Penalty (minutes)	Equivalent Cost (assuming $12/hr)
BETAs			
Car			
Dest - CBD Core	-2.6081	45.1	$ 9.02
Dest - CBD NonCore	-1.9468	33.7	$ 6.73
Dest - CBD Frame	-1.5573	26.9	$ 5.39
Dest - Outer Frame	-0.7710	13.3	$ 2.67

Table 9 - Destination Based Constants

Travelling by car to the CBD grid (referred to as CBD Core) incurs a penalty of 45 minutes, which is equivalent to $9, assuming a value of time of $12/hr. Given that this penalty is separately applied to both the outward (home to work) and return (work to home) trips, the total penalty associated with a return trip to the CBD Core is 90 minutes, or $18.

It is interesting to compare this value to the typical price of early bird parking in the CBD (in 2008), which we believe to have been approximately $13 (this figure is based on a desktop review conducted by VLC of the websites of off street parking operators, as they were in 2008).

Our work implies that the total perceived cost of parking in the CBD may be higher than the monetary $13. This may be due to:

- Time spent finding a car park
- Time spent walking from car park to destination
- Early bird constraints (arrive before a certain time, leave after a certain time)

It is also possible that our higher value is a result of some other factor unrelated to parking.

It is also worth noting that for certain commuters – specifically those who are provided a paid parking space by their employers – the perceived cost of parking is probably significantly less. In fact, such commuters may feel obliged to make use of the parking space, and act as a captive market for car travel. Such people most likely belong to particular income / occupation categories, and so it is likely that we can capture this effect in the future.

The estimated penalty decreases with distance from the CBD, with travel to the area immediately surrounding the CBD grid (CBD NonCore) incurring a 75% penalty relative to the CBD grid, with the CBD Frame and Outer Frame incurring penalties which are 60% and 30% of the CBD grid respectively.

4.1.2.5 Public Transport Transfers

Penalties for transfers between public transport modes have been estimated from the VISTA07 survey, and are presented in Table 10 below.

Transfer Penalties	Re-estimated	
	PARAMETER ESTIMATE	Equivalent Train Travel Time Penalty (minutes)
BETAs		
Public Transport		
Transfers - Tram / Tram	-1.0510	14.4
Transfers - Tram / Train	-1.9133	26.1
Transfers - Tram / Bus	-2.0264	27.7
Transfers - Train / Train	-0.8069	11.0
Transfers - Train / Bus	-2.2995	31.4
Transfers - Bus / Bus	-1.3164	18.0

Table 10 - Transfer Penalties

Generally speaking, the penalties for transfers within a mode (intra-modal transfers) are lower than inter-modal transfers.

Transfers within the train, tram and bus modes incur a penalty equivalent to 11, 14 and 18 minutes respectively. By contrast, the penalty for tram / train interchanging is 26 minutes, and 31 minutes for bus / train.

The intra-modal transfers (within modes) are probably slightly higher than the general norm. Transfer penalties of 5-10 minutes are typical, so 11 minutes for a train / train interchanging is slightly higher than expected.

Furthermore, the penalties for inter-modal transfers (between modes) are considerably higher than the accepted norm.

Nevertheless, the relativities between the penalties make some sense. It seems sensible that intra-modal interchange penalties should be lower, and the relativities between the train, tram and bus penalties are also intuitive.

In addition, these penalties have been estimated from a real survey of travel behaviour, and, in conjunction with the other variables included in the model, best explain the behaviour of the survey respondents.

One possible explanation is that the VISTA07 survey under-reports trips which involve interchanging. However, we ruled this out by calculating the number of mode to mode transfers from the VISTA survey (based on school term time only, MSD only), with the survey responses weighted to 2006 population estimates. We then compared these estimates with corresponding estimates of model transfers from the 2009/10 Rail OD Survey. The Rail OD survey is limited to transfers involving rail. The comparison is presented in Table 11 below.

From - To	VISTA07 MSD Only (weighted to 2006 pop)	2009/10 Rail OD Survey
Bus - Train	45,701	42,423
Tram – Train	49,213	37,949
Train – Bus	49,480	44,467
Train – Tram	53,086	47,432
Train – Train	86,884	74,236

Table 11 - Modal Transfers in the VISTA07 and 2009/10 Rail OD Survey

There is a reassuringly high level of correlation between the two surveys, though the VISTA07 survey is higher by an average of 15%, despite the fact that VISTA07 has been weighted to 2006, while the Rail OD survey is 2009/10. We think this is due to the OD survey interviews being restricted to those aged 16 and over, but are yet to confirm whether the interviews were weighted to include counts of persons aged 15 and under.

Irrespective, there is no evidence here that the VISTA07 survey under-reports transfers.

Given this, we intend to let the proof be in the pudding, so to speak, by including these transfer penalties in the model, and validating the rate of modal transfers against the Rail OD Survey. This will occur later in the process, and may result in a revision to this document.

4.1.2.6   Train Station Parking

For the first time, we have explicitly included train station parking as an explanatory variable in the Zenith model. The resulting model parameter is presented in Table 12 below.

Train Station Parking	Re-estimated	
	PARAMETER ESTIMATE	Equivalent Train Travel Time Saving per 100 car parks (minutes)
BETAs		
Public Transport - Car Access to Rail		
Train Station Parking	0.0039	5.3

Table 12 - Model Parameter for Train Station Parking for HBW

The important number is in the bottom right of the Table, and indicates that 100 car parks is worth approximately 5 minutes of rail travel time.

The factor applies to all car access trips, though clearly there should be a distinction between park 'n' ride trips, and kiss 'n' ride trips. If we were to separately model such trips, the parameter for station parking would be higher for park 'n' ride trips, and most likely zero for kiss 'n' ride trips.

We hope to separate park 'n' ride and kiss 'n' ride in the near future.

4.1.2.7 Modal Constants

Modal constants are included to capture everything else which isn't captured by the variables in the preceding sections. This can include but is not limited to general attitudes towards various modes.

The modal constants for HBW are presented in Table 13 below. In the second column, the constants have been expressed as a penalty (in terms of equivalent car travel time), while in the third column, the public transport sub-mode penalties have been normalised with rail penalties set to 5 minutes, and penalties for bus and tram expressed relative to this.

<u>Walking</u>

The constant for walking has been explicitly set to zero; constants are only meaningful in a relative sense, and so it is necessary to set one constant to zero. We have chosen walking.

<u>Car</u>

Working from the top, car has a penalty of approximately -4 minutes (a negative penalty indicates a saving). This indicates that for commuting trips (which by definition leave the home), car is on average preferable to walking by 4 minutes, after taking account the variables in the previous sections. For commuting travel this is believable.

<u>Cycling</u>

Cycling, on the other hand, has a large, negative penalty of 54 minutes. This indicates that for most of us, cycling is not the preferred method of travel to work, even if it is competitive in terms of travel time. Referring back to Section 4.1.2.1, it is interesting to note that the value of time for cycling travel was not overly high. It seems that the time spent cycling is not so much the problem; it is more that a certain level of motivation, fitness and commitment (ie. buying a bicycle) is required to make cycling an attractive option. Changing facilities at work also help! It is evident that a relatively small number of people overcome these obstacles.

Modal Constants	Re-estimated PARAMETER ESTIMATE	Equivalent Car Travel Time Penalty (minutes)	Normalised PT Penalties (minutes)
Constants			
Car			
Car	0.2177	-3.8	
Cycling			
Cycling	-3.1228	54.0	
Public Transport			
Walk <=> train	-1.6451	28.5	*5.0*
Walk <=> tram	-1.9748	34.2	10.7
Walk <=> bus	-2.8788	49.8	26.3
Car <=> train	-8.1133	140.3	*5.0*
Car <=> tram	-9.3809	162.3	26.9
Car <=> bus	-10.1124	174.9	39.6
BETAs			
Public Transport			
Regional Bus	-0.4631	8.0	
Smart Bus	0.5045	-8.7	

Table 13 - Modal Constants for HBW

Public Transport

The penalties for public transport are also substantial. Walking to or from train, tram and bus incurs a penalty of 29, 34 and 59 minutes respectively. It should be noted that these penalties are applied on both access and egress, even for trips with a single public transport leg.

For example, a trip involving *Walk => Train => Walk* will incur a penalty of 57 minutes (2 x 28.5).

The scale of these penalties suggests that the perceived cost of using public transport is significantly more than just the walking time, waiting time, in-vehicle time, fare, etc, which we have already included in the model. This cost relates to factors which are currently *unobserved* in the model, such as:

- A lack of knowledge and awareness about the public transport system
- The added complexity of making a public transport trip (ie. extra planning required)
- A lack of real time information
- Unreliability
- A lack of flexibility in onward travel (ie. by taking a car, you have greater options for travel following your current trip)
- A fixed timetable means that you may not arrive or depart exactly when you want
- A preference against travelling with other people

The list could go on.

From a modelling point of view, the penalty indicates that all other things being equal, people will tend not to take public transport (a proportion will, of course).

In other words, if the cost of public transport and car are equal after taking account of all of the modelled variables (travel time, fuel, fare, parking, transfers, household car ownership etc), then a majority of people will opt to travel by car. This is due to unobserved factors, some of which we have speculated about above.

Going forward, it should be our aim to reduce these penalties, by including (where possible) some of the variables which are currently unobserved.

It is normal to decompose this penalty into two parts: one part which applies to walk access to transit generally, and one part which is sub-mode specific.

For example, if we apply a general penalty of 23.5 minutes to walk access to transit, then an additional penalty of 5 minutes would apply to train, 10.7 minutes to tram and 26.3 minutes for bus. We call these normalised PT penalties, and they are presented in the right most column of Table 13 above. Note that the choice of 5 minutes for train is arbitrary; we could just as easily have chosen 15 minutes, and reduced the general walk access penalty to 13.5 minutes. This explains why the Zenith access penalties have traditionally been higher than those in MITM. We simply chose a different arbitrary penalty for train.

This also implies that only the differences in penalty matter; penalties of 5, 10.7 and 26.3 are equivalent to 15, 20.7 and 36.3.

It is interesting to compare these penalties to those used in the current Zenith model.

Modes	Re-estimated Model	Re-estimated Difference from Train	Current Zenith Model	Current Difference from Train
Walk <=> train	5.0		12.0	
Walk <=> tram	10.7	5.7	17.0	5.0
Walk <=> bus	26.3	21.3	29.0	17.0
Car <=> train	5.0		22.5	
Car <=> tram	26.9	21.9	46.0	23.5
Car <=> bus	39.6	34.6	51.0	28.5

Table 14 - Comparison of Re-estimated and Current Access Penalties

Referring to Table 14 above, it can be seen that the differences in penalties between the various public transport modes are very similar between the re-estimated and current Zenith model. The difference between walk ⇔ train and walk ⇔ tram is approximately 5 minutes in both the re-estimated and current models. The difference between walk ⇔ train and walk ⇔ bus is 21 minutes in the re-estimated model and 17 minutes in the current model (this is consistent with the higher penalty / lower in-vehicle time weight theory outlined for bus in Section 4.1.2.1).

The pattern is almost identical for car access to transit.

This provides some scientific justification for the penalties which are currently in the model. This is reassuring, as the current penalties were tuned to enable the model to match observed demands on the three modes.

Regional Bus & Smart Bus

We have also estimated a constant penalty for regional bus and smart bus, which apply in addition to the walk ⇔ bus and car ⇔ bus penalties. These penalties represent a difference between regional bus / smart bus, and other busses.

Smart bus is found to have a negative penalty of around 9 minutes. This indicates that smart bus is more attractive than a regular bus by a constant offset of 9 minutes. Conversely, regional bus has a penalty of 8 minutes, indicating that regional busses are less attractive than regular busses.

It should be noted that there is some uncertainty in these estimates, which is a result of a lack of sample. This is illustrated by their p-values of 0.15 and 0.18 respectively. These p-values indicate that given our sample, there is a 15% chance that the smart bus parameter could come out as it has even if smart busses are identical to normal busses.

Nonetheless, the parameters are intuitive, and so we have opted to retain them, and then refine them by pooling VISTA07 and VISTA09 at a later date.

Also note that unlike the other public transport penalties, which are applied on both access and egress, the penalties for smart bus and regional bus are only applied on access.

4.1.3   Model Validation

The Mode Choice model has been validated by applying the model to the VISTA07 survey respondents, and comparing our predictions of mode choice with their actual, reported mode choice decisions.

Three types of validation are provided:

- Overall
- By period
- Demographic
- Spatial

4.1.3.1   Overall Model Validation

Applying the model to the VISTA07 survey respondents, we can compare the reported mode shares across all respondents with our predicted mode shares, as presented in Table 15.

Average Mode Shares
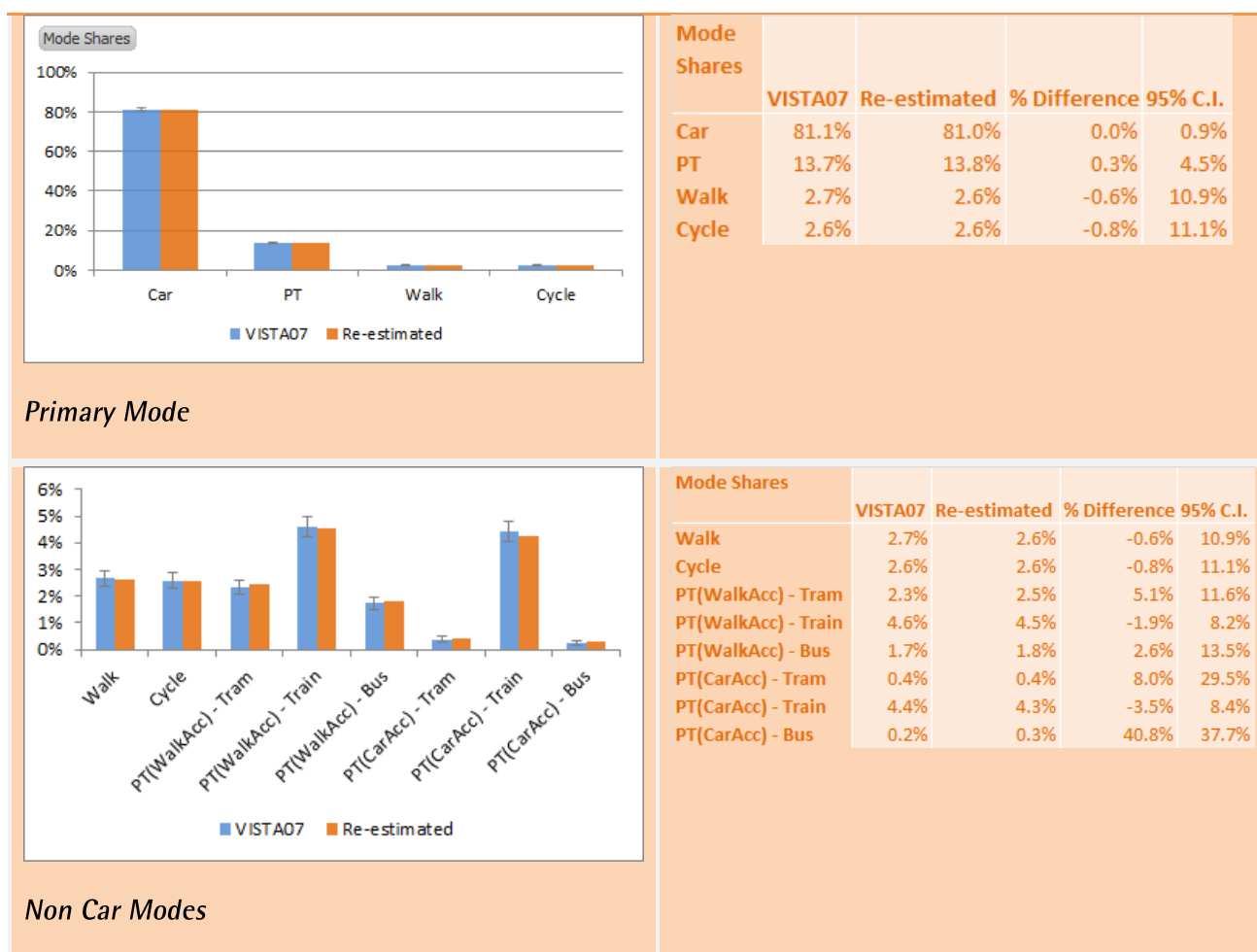Home Based Work | Re-estimated Zenith Model

Primary Mode

Mode Shares	VISTA07	Re-estimated	% Difference	95% C.I.
Car	81.1%	81.0%	0.0%	0.9%
PT	13.7%	13.8%	0.3%	4.5%
Walk	2.7%	2.6%	-0.6%	10.9%
Cycle	2.6%	2.6%	-0.8%	11.1%

Non Car Modes

Mode Shares	VISTA07	Re-estimated	% Difference	95% C.I.
Walk	2.7%	2.6%	-0.6%	10.9%
Cycle	2.6%	2.6%	-0.8%	11.1%
PT(WalkAcc) - Tram	2.3%	2.5%	5.1%	11.6%
PT(WalkAcc) - Train	4.6%	4.5%	-1.9%	8.2%
PT(WalkAcc) - Bus	1.7%	1.8%	2.6%	13.5%
PT(CarAcc) - Tram	0.4%	0.4%	8.0%	29.5%
PT(CarAcc) - Train	4.4%	4.3%	-3.5%	8.4%
PT(CarAcc) - Bus	0.2%	0.3%	40.8%	37.7%

Table 15 – Overall Mode Shares for Home Based Work

At the level of primary modes there is excellent agreement between the Zenith Mode Choice model, and the VISTA07 survey. Predicted mode shares are within 1% in all cases. This is well within the 95% confidence intervals (95% C.I.), which range from 1% for car, to 11% for walking and cycling.

A more detailed breakdown is also provided for non-car modes. Again, there is excellent agreement between the model and survey, with differences falling well within 95% confidence intervals on the true average mode shares, with the exception of car access to bus, which represents only 0.2 % of trips.

4.1.3.2   By Period Validation

A comparison has been made of *by period* mode shares in VISTA07 with predicted mode shares from the Zenith Mode Choice model. This comparison is presented in Table 16 below.

It can be observed that public transport mode shares are significantly higher in the peaks (16.7% and 16.5% in the AM and PM peaks, compared with 10% in the off peak). Car mode shares show an opposite pattern. This is thought to be caused by a combination of effects: a higher proportion of CBD based commuters in the peaks, and generally higher level of service for public transport in the peaks (higher frequencies), and conversely lower level of service for car travel in the peaks (higher congestion, slower traffic speeds).

The model does an excellent job of reproducing this pattern, which is encouraging given that the model does not have any constants associated with specific periods. The model seems to explain variations in mode share across the day in terms of variations in travel costs, and variations in travel patterns (ie. higher proportion of CBD based travel in the peaks).

Cycling mode shares also vary across the day, and are highest during the peaks. The model also does an excellent job of predicting this pattern.

Average Mode Shares by Period
Home Based Work | Re-estimated Zenith Model
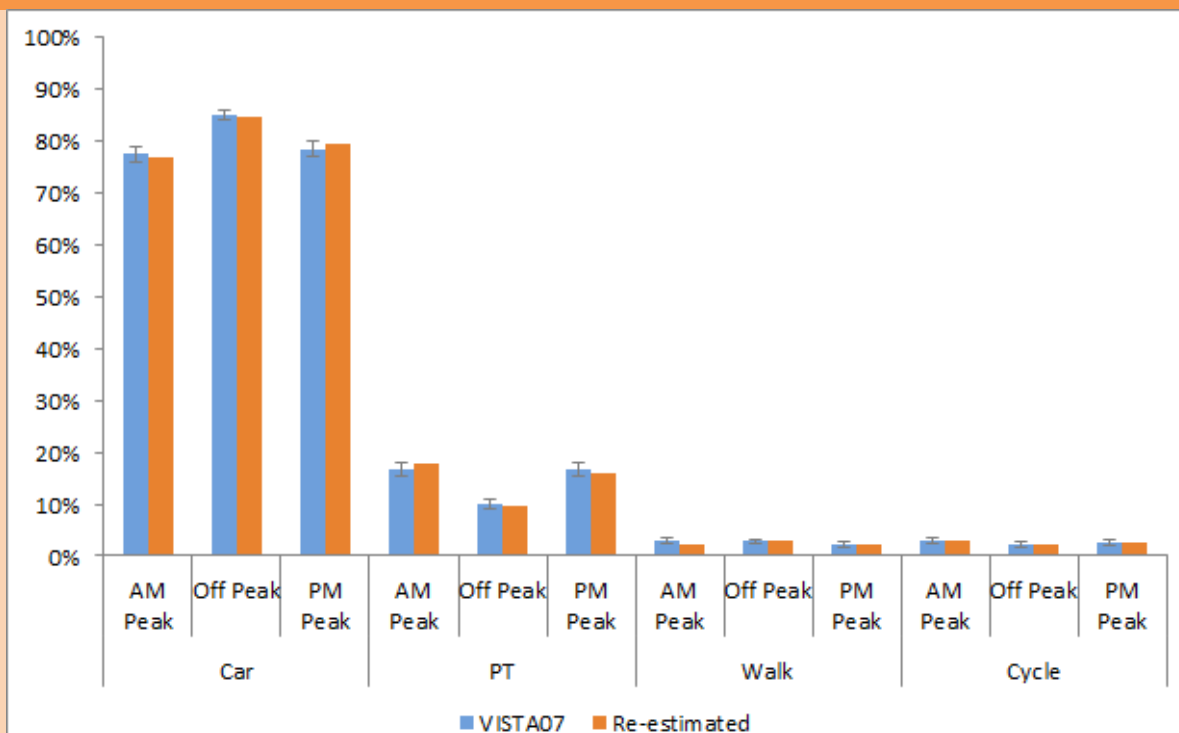
Mode Share by Period	VISTA07	Re-estimated	% Difference	95% C.I.
Car				
AM Peak	77.5%	77.0%	-0.6%	±1.8%
Off Peak	85.0%	84.8%	-0.3%	±1.1%
PM Peak	78.5%	79.4%	1.2%	±1.8%
PT				
AM Peak	16.7%	17.8%	6.3%	±7.4%
Off Peak	10.0%	9.8%	-1.9%	±8.2%
PM Peak	16.5%	15.8%	-4.2%	±7.9%
Walk				
AM Peak	2.9%	2.4%	-16.6%	±19.2%
Off Peak	2.8%	3.1%	12.4%	±16.1%
PM Peak	2.2%	2.1%	-4.1%	±23.2%
Cycle				
AM Peak	2.9%	2.8%	-3.6%	±18.9%
Off Peak	2.2%	2.3%	4.5%	±17.9%
PM Peak	2.7%	2.6%	-4.5%	±21%

Table 16 - Mode Shares by Period (HBW)

4.1.3.3 Demographic Validation

The re-estimated Zenith Mode Choice model has been applied to the survey respondents, with predicted and survey mode shares grouped by a series of demographic variables, namely:

- Household car ownership
- Household income
- Occupation

Each is now discussed.

<u>Household Car Ownership</u>

A comparison of VISTA07 and predicted mode shares by household car ownership level is presented in Table 17 below. It can be observed that car mode shares increase as household car ownership rises from 0 to 1, and then 1 to 2, but plateaus from there onwards. This is consistent with our model estimation process, which found no difference between two and three car households in terms of mode choice for Home Based Work (there may be a difference in other trip purposes).

Unsurprisingly, public transport mode shares are highest for 0 car households, averaging nearly 60% of all trips. Walking and cycling is also most prevalent among 0 car households.

The model does an excellent job of predicting these outcomes. Car mode shares are within 1% at all levels, though this is largely a result of car ownership being included as a variable in the car utility (see Section 4.1.2.3).

The public transport mode share for 0 and 1 car households is predicted to within 3%, while 2 and 3 car households are predicted to within 10%. This is to be expected as 2 and 3 car households have a lower public transport mode share, which introduces greater relative uncertainty in the survey estimates.

Average Mode Shares by Household Car Ownership Level
Home Based Work | Re-estimated Zenith Model
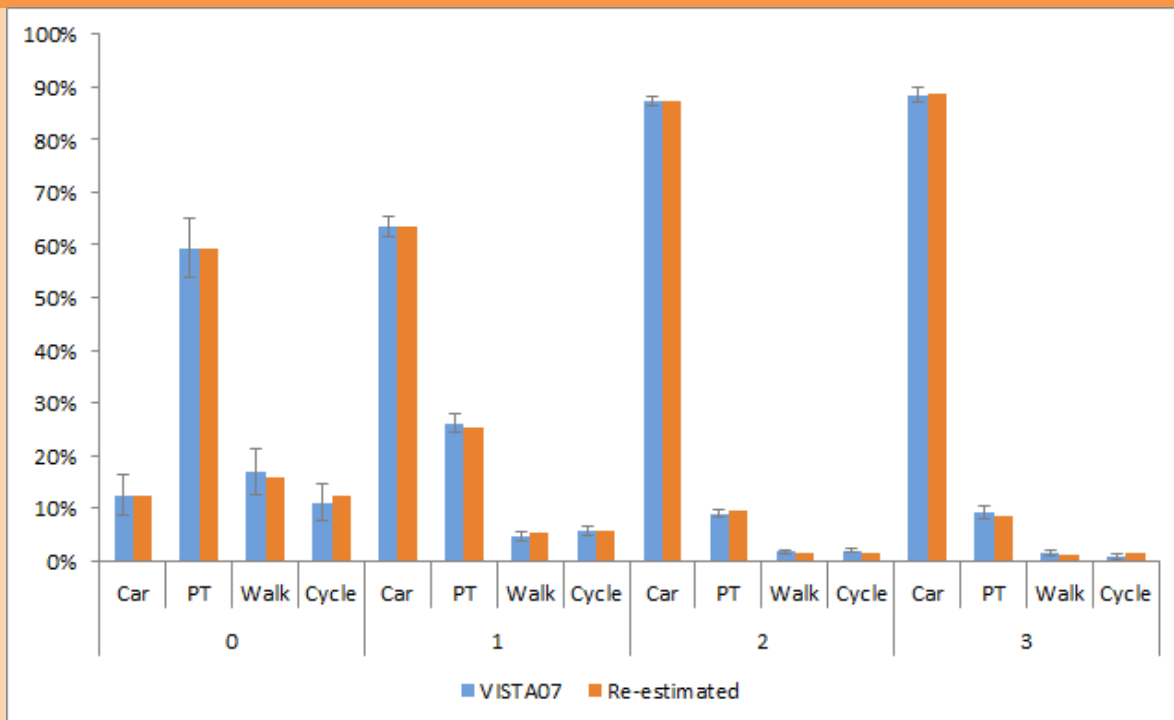
Mode Share by Car Ownership	VISTA07	Re-estimated	% Difference	95% C.I.
0				
Car	12.5%	12.5%	0.1%	±30.6%
PT	59.4%	59.2%	-0.4%	±9.6%
Walk	17.0%	15.8%	-6.9%	±25.6%
Cycle	11.1%	12.5%	12.3%	±32.7%
1				
Car	63.4%	63.4%	0.0%	±3%
PT	26.2%	25.4%	-2.7%	±6.6%
Walk	4.7%	5.5%	15.7%	±17.7%
Cycle	5.7%	5.7%	-0.7%	±16%
2				
Car	87.4%	87.4%	0.0%	±1%
PT	9.0%	9.5%	5.9%	±8.2%
Walk	1.7%	1.6%	-7.1%	±19.6%
Cycle	1.9%	1.5%	-22.6%	±18.4%
3				
Car	88.4%	88.8%	0.5%	±1.6%
PT	9.3%	8.5%	-8.4%	±13.4%
Walk	1.5%	1.3%	-16.7%	±34.4%
Cycle	0.8%	1.4%	80.2%	±48.8%

Table 17 - Mode Shares by Household Car Ownership Level (HBW)

Household Income

A comparison of VISTA07 and predicted mode shares by income level is presented in Table 18 below.

It can be seen that car mode shares form an umbrella shape, peaking for middle income households. Car mode shares are lower for low income households, and also for high income households. Public transport mode shares take the opposite pattern. The effect is not enormous, with mode shares in VISTA07 ranging from 78-80% for the highest and lowest income households, to around 84% for middle income households.

The low car usage (and high PT usage) of low income households is most likely a result of low car ownership. This is demonstrated in Figure 16, immediately below, which demonstrates that low income households are much more likely to own 0 or 1 car than higher income households.
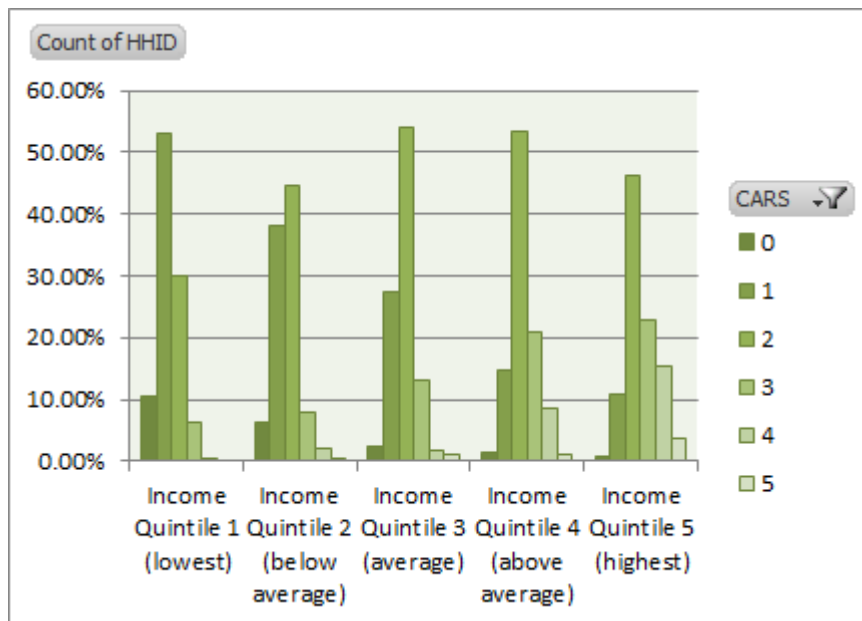
Figure 16 - Household Car Ownership by Income Level (VISTA07)

Average Mode Shares by Income Level
Home Based Work | Re-estimated Zenith Model
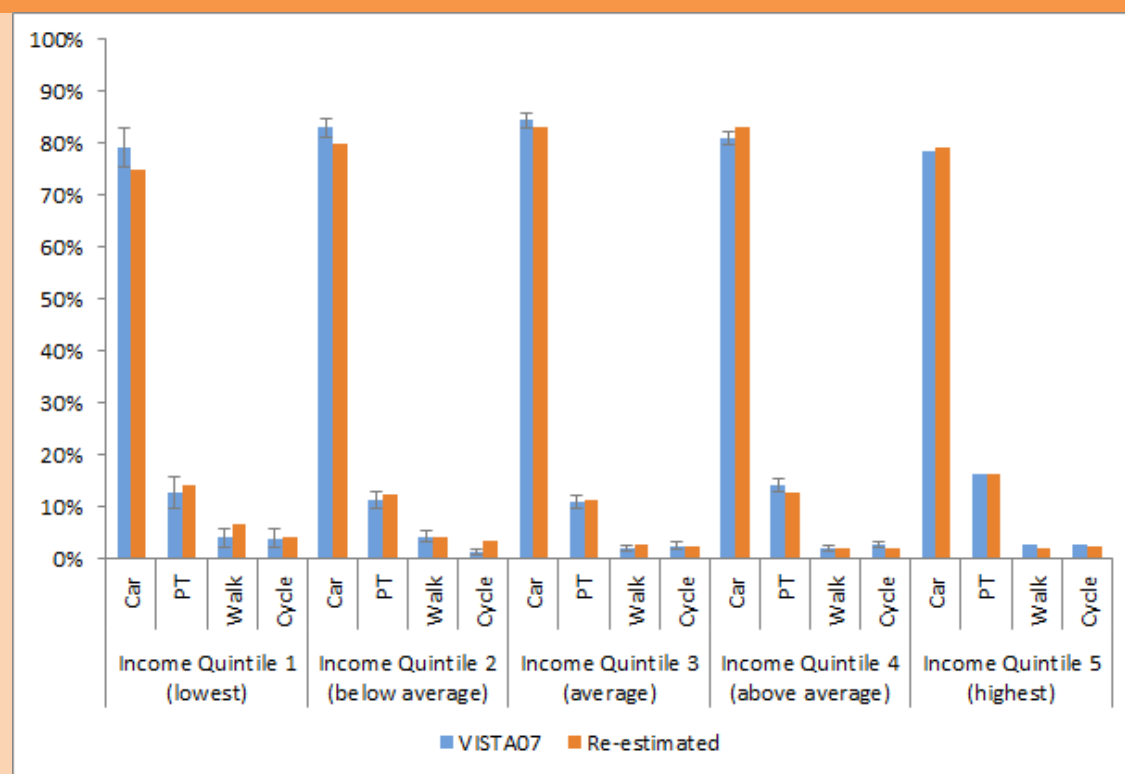
Mode Share by Income Level	VISTA07	Re-estimated	% Difference	95% C.I.
Income Quintile 1 (lowest)				
Car	79.3%	74.8%	-5.7%	± 4.7%
PT	12.7%	14.2%	11.8%	± 23.9%
Walk	4.1%	6.7%	64.4%	± 44.1%
Cycle	3.9%	4.3%	10.1%	± 45.3%
Income Quintile 2 (below average)				
Car	83.0%	79.8%	-3.8%	± 2.3%
PT	11.3%	12.6%	10.7%	± 14%
Walk	4.4%	4.3%	-1.4%	± 23.4%
Cycle	1.3%	3.3%	155.5%	± 43.6%
Income Quintile 3 (average)				
Car	84.4%	83.2%	-1.5%	± 1.6%
PT	11.0%	11.5%	4.9%	± 10.9%
Walk	2.0%	2.8%	36.4%	± 26.4%
Cycle	2.6%	2.5%	-1.7%	± 23.5%
Income Quintile 4 (above average)				
Car	80.9%	83.0%	2.5%	± 1.6%
PT	14.2%	12.9%	-9.1%	± 8.3%
Walk	2.1%	1.9%	-7.2%	± 23.2%
Cycle	2.8%	2.2%	-22.4%	± 19.8%
Income Quintile 5 (highest)				
Car	78.3%	79.2%	1.2%	± 1.7%
PT	16.2%	16.3%	0.8%	± 7.2%
Walk	2.8%	2.0%	-26.1%	± 18.8%
Cycle	2.7%	2.4%	-11.5%	± 18.9%

Table 18 - Mode Shares by Income Level (HBW)

The low car usage (and high PT usage) of high income households is likely a result of where they work. High income earners are more likely to work in the CBD. This is illustrated in Figure 17 below which shows the breakdown of trips to the Melbourne (Inner) SLA, by income level. Nearly half of all HBW trips to this SLA are made by households from the highest income quintile, despite these households representing only 20% of all households.
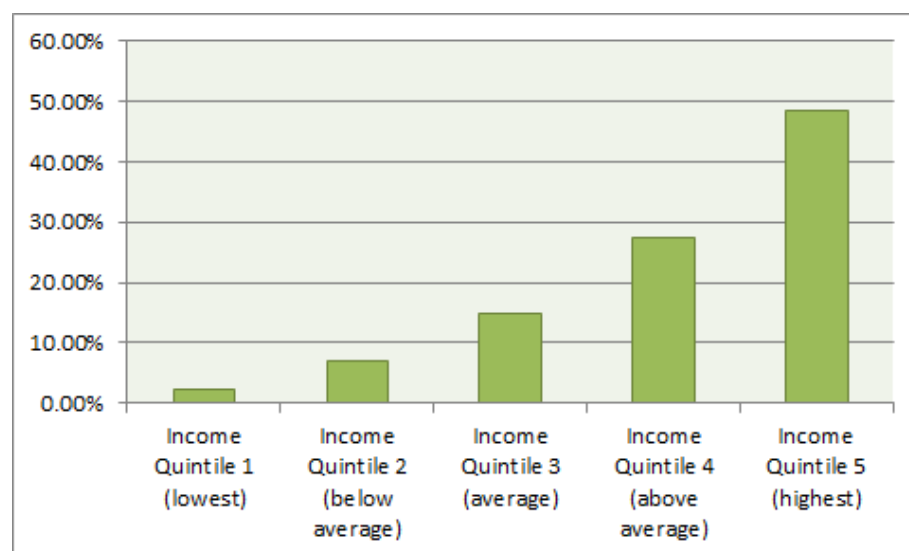

Figure 17 - Breakdown of HBW Trips to Melbourne (Inner) SLA by Income Level (VISTA07)

The model does quite a good job of replicating this pattern, but it does appear to systematically under-estimate car usage (and over-estimate PT usage) for low income households, and vice versa for high income households.

This has a very interesting explanation which highlights a current limitation of the model. The effect of household car ownership on the attractiveness of car travel is fixed across all households (as it is currently modelled). As expected, owning 0 cars makes car travel very unattractive, while owning 1 car has a moderate negative effect. However, in reality, the effect of car ownership varies by household type.

For example, the effect of owning one car on a family with 2 workers and 3 children will be profoundly different to the effect of owning one car on a single person household.

Clearly, it is car availability, not car ownership, that truly effects mode choice decisions.

A common form of car competition is between workers in the household.
Take two households:
1. 1 worker, 1 car – *the worker will most likely have access to the car, resulting in high car use*,
2. 2 workers, 1 car - *one must compromise and take another mode (or else be dropped off by someone else)*.

Clearly, these households types will exhibit different mode shares, with higher car use in the first household type. However, the model would treat both households equally – as 1 car households.

The result is that the model will include an average effect of owning one car, and thus predict a mode share somewhere in between, under-estimating the car use of the first household type, and over-estimating for the second household type.

Now, think back to our low income households. Low income households have low car ownership, which should (and does) have a negative effect on car use. However, they also have a low number of workers (as illustrated in ....). As a result, there is reduced car competition in low income households, dampening the effect of owning only one car.

The model, however, treats all low car households equally, and over-penalises car use for these households. As a result, the model under-predicts car usage for low income households. The converse is true for high income households.
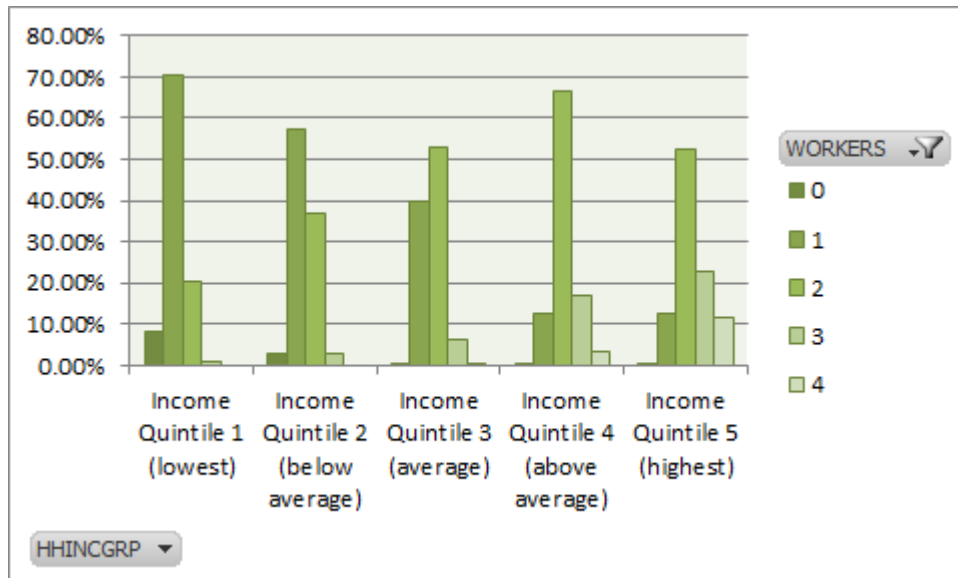
Figure 18 - Number of Workers, by Household Income Level (VISTA07)

We hope in the near future to account for car competition explicitly in the Zenith model. However, we will first need to move towards a disaggregate model that explicitly models discrete people and households.

<u>Occupation</u>

A comparison of VISTA07 and predicted mode shares by income level is presented in Figure 21 and Table 19 below.

It can be seen that Managers, Professionals and Clerical and Administrative Workers have the highest public transport mode shares. This is a result of these jobs being more commonly located in the inner city.

Figure 21 below clearly illustrates a clear relationship between the proportion of jobs located in the inner city for and overall public transport mode share for an occupation. Occupations with a high proportion of workers in the inner city also have high public transport mode shares.
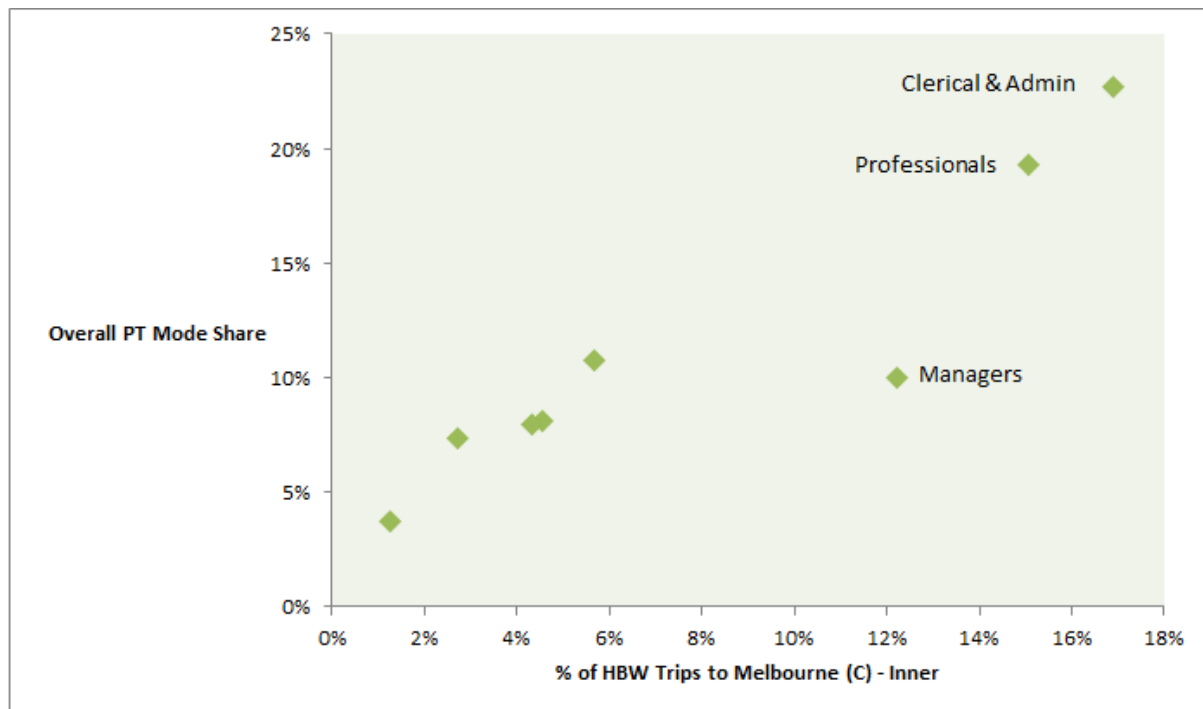
Figure 19 - Public Transport Mode Share by % of HBW Trips to the Melbourne (Inner) SLA (VISTA07)

A notable outlier is the set of Managers, who have a lower than expected public transport mode share, given the number of Managers who work in the Inner City. It is also notable that the model fails to predict this outcome, while accurately predicting the mode shares of all other occupations.

This has an interesting explanation which highlights another limitation of the model.

Managers are unique in that they are more likely to have access to a reserved (and perhaps paid for) car park at their work place. As a result, Managers are much more likely to drive, and thus exhibit a lower than expected public transport mode share.

This effect is most pronounced in areas of short parking supply, most notably the inner city. In Figure 20 below it can be seen that the mode share for public transport to the Melbourne Inner SLA (ignoring walk and cycle) is roughly 70 to 90% for all occupations except Managers, of whom only half travel by public transport.
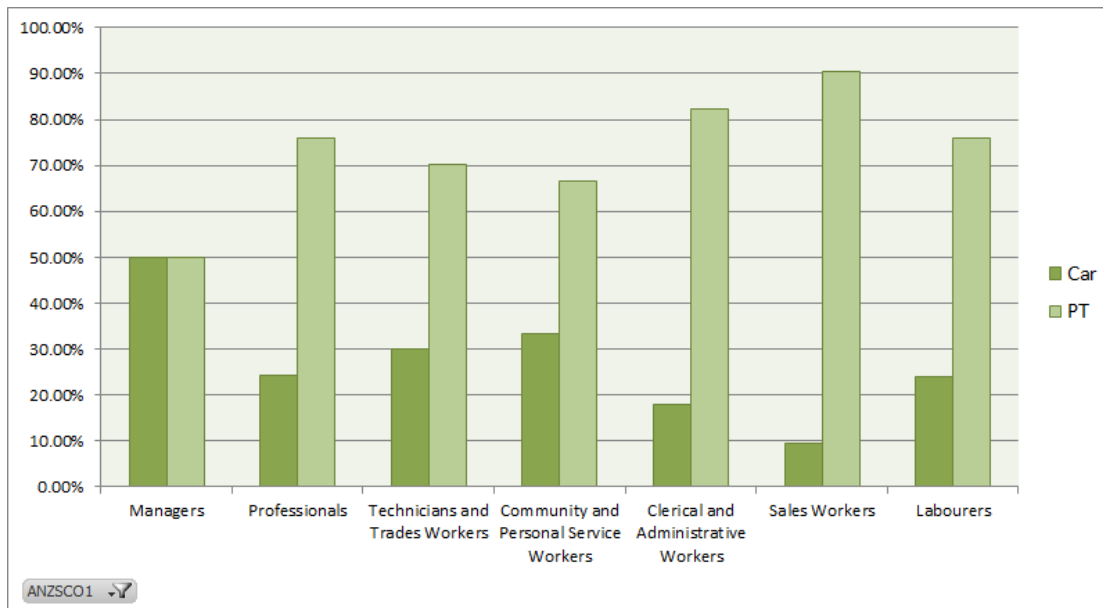
Figure 20 - Split between Car and Public Transport for Trips to the Melbourne Inner SLA (VISTA07)

We hope in the near future to account for car park availability explicitly within the model. At that time we will further explore the relationship between occupation (and potentially income) on access to reserved parking.

Average Mode Shares by Occupation
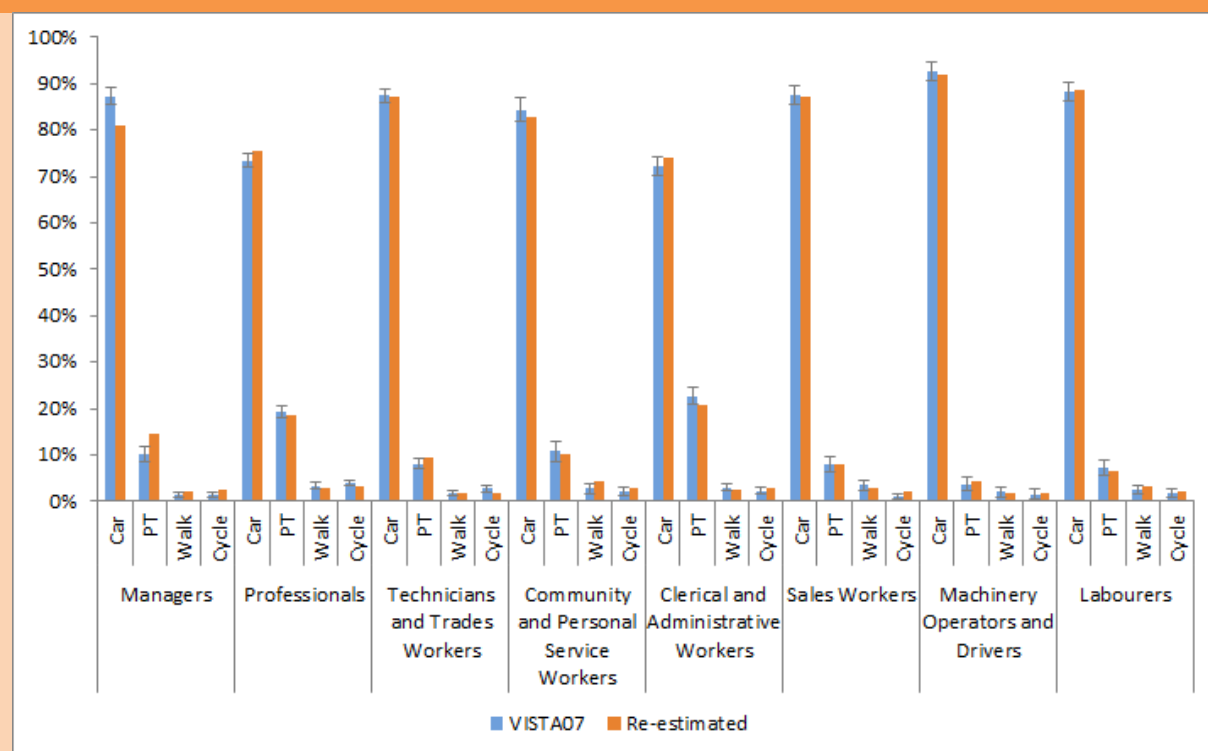Home Based Work | Re-estimated Zenith Model

Figure 21 – Comparison of VISTA07 and Zenith Mode Shares by Occupation (HBW)

Mode Share by Occupation	VISTA07	Re-estimated	% Difference	95% C.I.
Managers				
Car	87.2%	80.9%	-7.2%	±2.1%
PT	10.0%	14.6%	46.1%	±16.5%
Walk	1.4%	2.0%	40.6%	±45.9%
Cycle	1.3%	2.4%	81.7%	±47.2%
Professionals				
Car	73.4%	75.3%	2.6%	±2%
PT	19.3%	18.5%	-4.1%	±6.9%
Walk	3.4%	3.0%	-11.9%	±18.1%
Cycle	4.0%	3.3%	-18.2%	±16.6%
Technicians and Trades Workers				
Car	87.5%	87.0%	-0.6%	±1.7%
PT	8.1%	9.4%	15.3%	±15.2%
Walk	1.6%	1.9%	17.5%	±34.9%
Cycle	2.8%	1.7%	-37.7%	±26.8%
Community and Personal Service Workers				
Car	84.4%	82.9%	-1.8%	±3%
PT	10.7%	10.2%	-5.1%	±20.1%
Walk	2.8%	4.2%	50.1%	±41.2%
Cycle	2.1%	2.8%	30.7%	±47.1%
Clerical and Administrative Workers				
Car	72.2%	74.1%	2.7%	±2.8%
PT	22.7%	20.7%	-8.9%	±8.4%
Walk	2.9%	2.3%	-19.2%	±26.3%
Cycle	2.3%	2.9%	29.0%	±29.9%
Sales Workers				
Car	87.6%	87.2%	-0.4%	±2.3%
PT	8.0%	8.0%	0.0%	±21.2%
Walk	3.4%	2.8%	-18.0%	±33%
Cycle	1.0%	2.0%	98.6%	±61.7%
Machinery Operators and Drivers				
Car	92.7%	92.1%	-0.6%	±2.2%
PT	3.8%	4.4%	17.1%	±39.3%
Walk	2.0%	1.9%	-6.4%	±53.8%
Cycle	1.6%	1.6%	4.2%	±61.5%
Labourers				
Car	88.3%	88.5%	0.2%	±2.4%
PT	7.3%	6.4%	-12.9%	±23.1%
Walk	2.5%	3.0%	21.3%	±40.4%
Cycle	1.9%	2.1%	12.9%	±47.1%

Table 19 – Comparison of VISTA07 and Zenith Mode Shares by Occupation (HBW)

4.1.3.4   Spatial Validation

The re-estimated Zenith Mode Choice model has been applied to the survey respondents, with predicted and survey mode shares compared at a number of different levels of spatial aggregation, namely:

- Travel zone
- LGA

We also examine the models predictions by trip length.

4.1.3.4.1   Travel Zone

We have made a comparison of reported VISTA07 public transport trips with public transport trips predicted by the model, at the level of individual travel zones. Due to a lack of sample (and lack of public transport trips in general), it is only meaningful to make this level of comparison for travel zones in the inner city.

The comparison is presented in Figure 22 below. The left most (dark blue) bar represents the total number of HBW trips made to each travel zone in VISTA07 (summed across all modes). The second bar (light blue) represents the HBW trips made by public transport in VISTA07. The height of the second bar to the first bar is a measure of public transport mode share. To the CBD, the mode share is generally around 75%. The third (orange) bar represents the public transport trips predicted by the Zenith model, having applied the mode choice model to all VISTA07 trips. If the model was a perfect predictor of mode choice, then the light blue and orange bars would be of equal height. Each bar has a label which indicates the number of trips.

It appears that in general, the model is an accurate predictor of mode shares, even at the zonal level. There are unders and overs, but it must be remembered that we are dealing with very small samples, typically between 10 and 40 trips for travel to the major CBD travel zones.
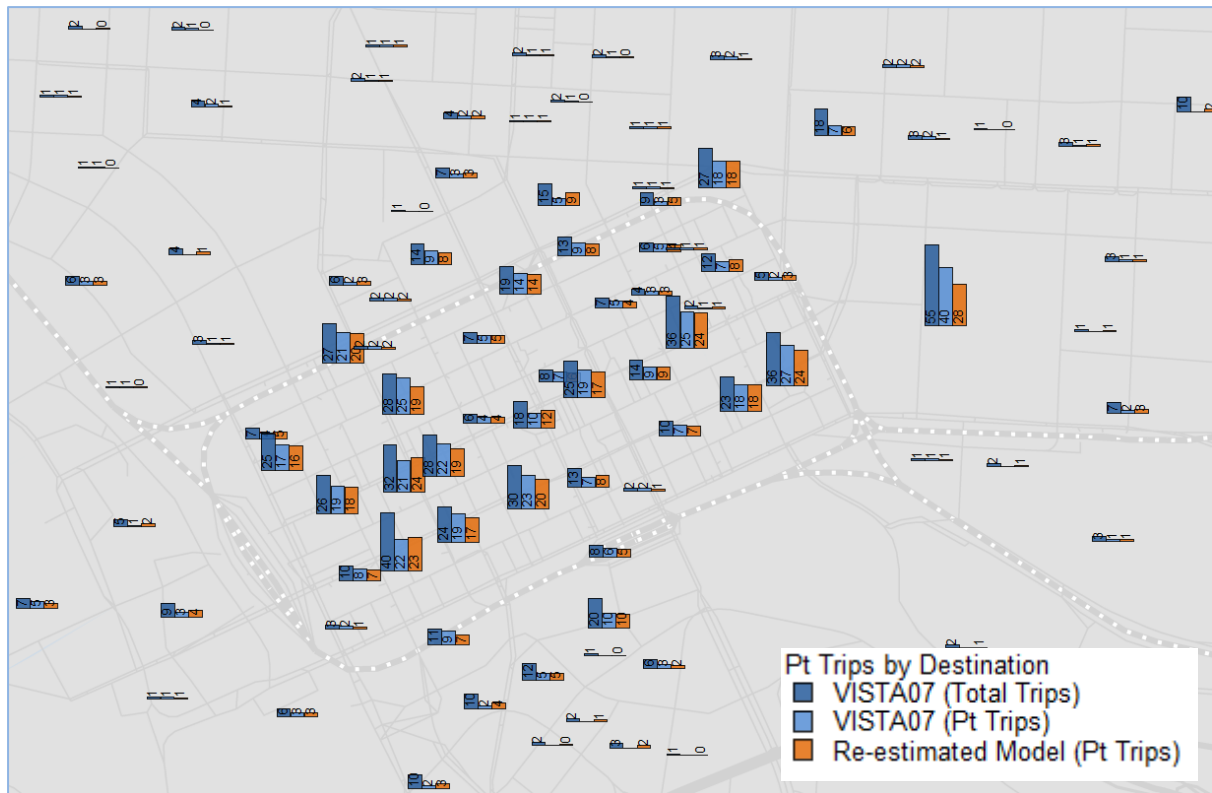
Figure 22 - VISTA07 and Modelled Pt Trips by VLC Travel Zone (HBW)

4.1.3.4.2   LGA

We have analysed the performance of the mode choice model at the level of individual LGAs.

We first examined the mode share of each LGA as a *destination* (attractor, or work end) of HBW trips.

In Figure 23 below, the left most (dark blue) bar represents the total reported HBW trips destined for each LGA in VISTA07. The second (light blue) bar represents the number of these trips which were made by public transport in VISTA07. The orange bar is the number of predicted public transport trips, when applying the mode choice model to the VISTA07 survey respondents.
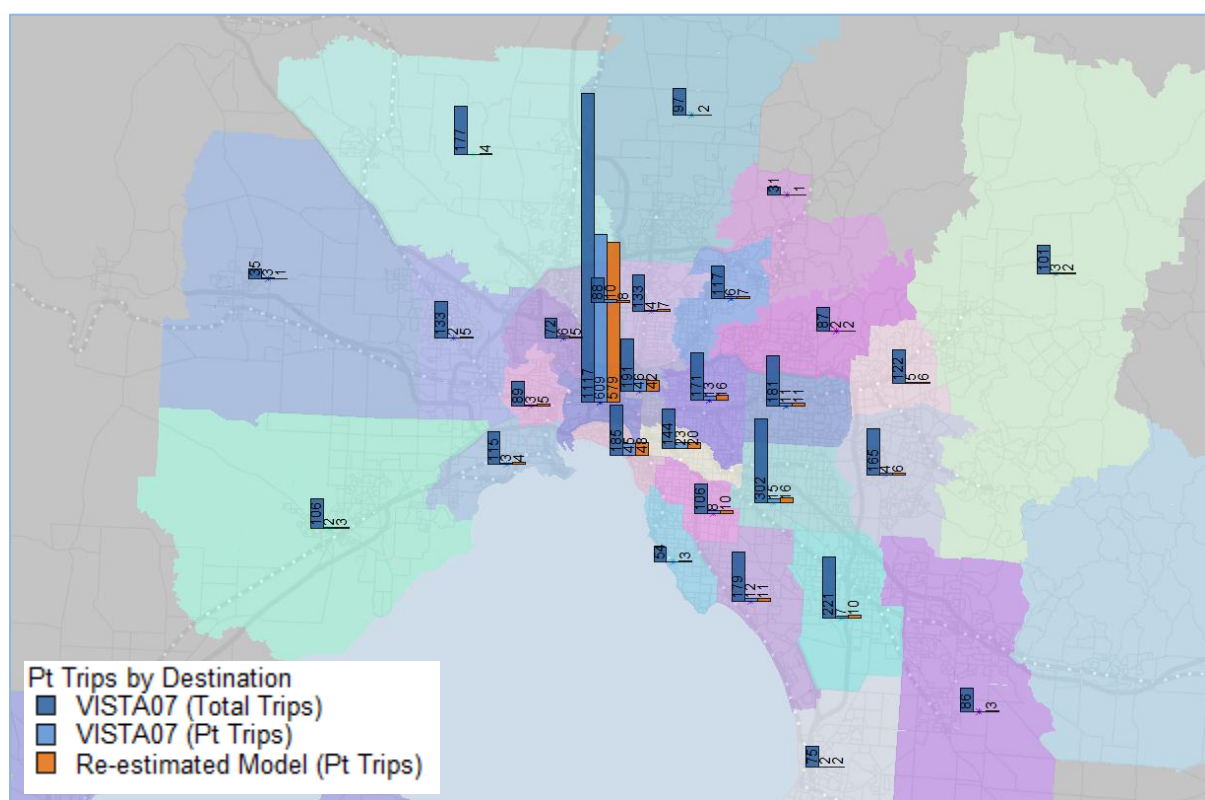
Figure 23 - VISTA07 and Modelled Pt Trips by LGA (HBW)

Public transport mode shares are highest in the inner city, and decrease with distance from the CBD. The model appears to replicate this pattern.

This is illustrated in Figure 24 below, which demonstrates that the model closely matches public transport mode shares to each LGA. An R–Squared of 0.97 is achieved, or 0.88 if the Melbourne LGA is removed (as seen in the inset). The gradient is 0.96, which indicates that the model has a slight tendency to under-predict public transport mode shares for LGAs which have a high mode share (eg. 51% vs 53% for the Melbourne LGA), and slightly over-predict for LGAs with very low mode shares.
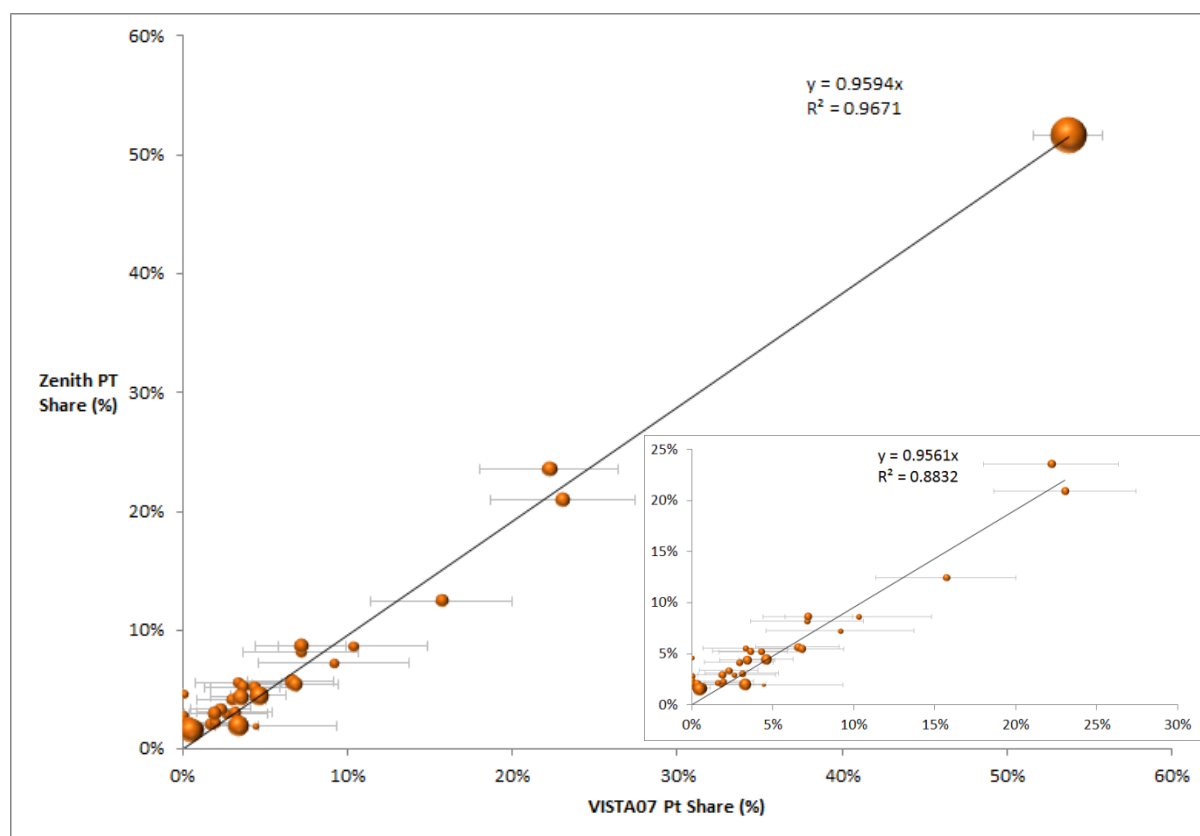
Figure 24 - Public Transport Mode Share by Destination LGA (HBW)

Given the importance of the Melbourne LGA as a destination for public transport trips, we have examined the public transport mode share from each individual LGA to the Melbourne LGA.

This analysis is presented in the form of desire lines, in Figure 25 below. Orange indicates that the model is predicting more public transport trips than were reported in VISTA07; blue indicates the opposite. The grey part of the desire line indicates agreement between the model and survey (we want the grey to dominate, with little orange or blue). The numbers indicate the percentage difference between Zenith and the VISTA07 survey.

It appears that the model is doing an excellent job of predicting public transport demands from a wide variety of origins to the Melbourne LGA. There is, however, an observable pattern of slight under-prediction from the inner and middle, eastern and south-eastern LGAs, with slight over-prediction from the west, and from the very outer LGAs.

This has a very interesting explanation which highlights a weakness in our treatment of station parking (a weakness which we hope to rectify shortly).

We have introduced a parameter which is linear with the off-street parking at a train station. The scale of the parameter is such that 100 car parks is worth approximately 5 minutes of car travel time.
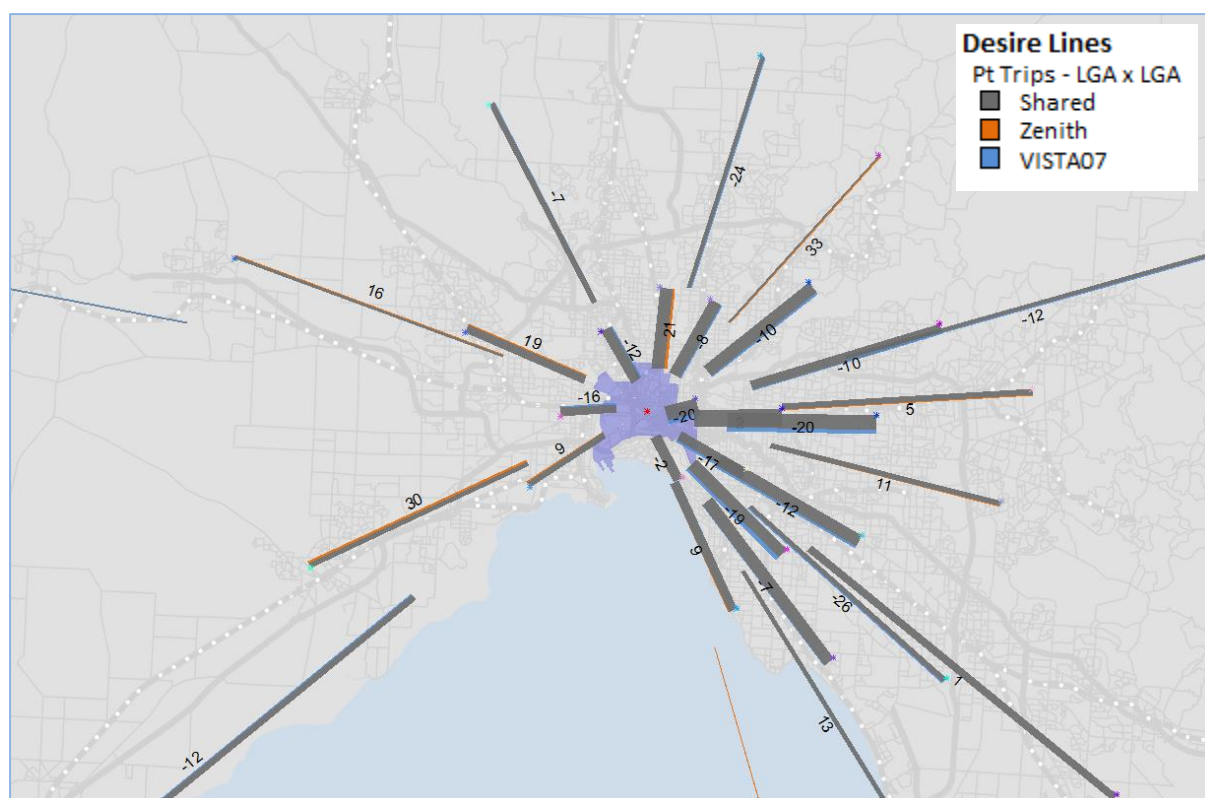
Figure 25 - Public Transport Trips to the Melbourne LGA, in VISTA07 and Zenith (HBW)

However, the number of parking spaces at a station is not the sole determinant of whether parking at the station is attractive. The degree of competition for those parking spaces plays a key role.

Take a hypothetical example.

Imagine replacing a single station, with 1000 car parks, with 5 closely packed stations each with 400 car parks.

According to our model, the station with 1000 car parks will be very attractive, and the 5 closely packed stations less so. In the model, car access demand would reduce in the scenario with 5 stations.

However, it is clear that overall parking supply has doubled in the case of the 5 stations. This should cause overall car access demand to increase, rather than decrease. This is especially so given that park 'n' ride trip makers are mobile and can easily reach nearby stations.

It is this effect which causes the model to under-predict travel from the east and south east.

As seen in Figure 26 below, there is a very large overall supply of parking in the east and south east (Burnley and Caulfield groups, respectively). By contrast, the Clifton Hill and Northern lines have significantly less parking.

This is further illustrated in Table 20, which highlights that the east and south east are served by a combined parking supply in excess of 17,000. By contrast, the west and north are served by a combined supply of roughly 10,000.
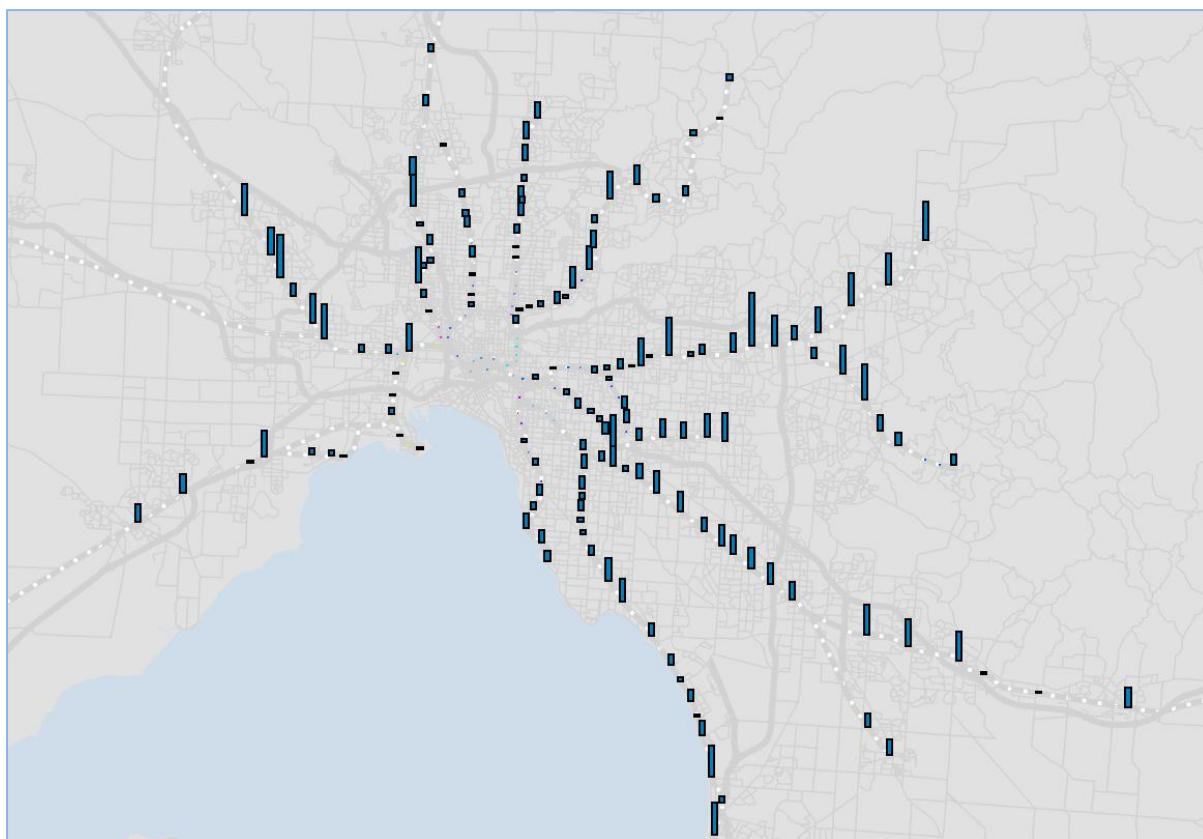
Figure 26 – Off Street Train Station Parking Supply

Station Line Group	Total Parking Supply
Burnley	8,520
Caulfield	8,498
Clifton Hill	3,576
Northern	6,331
City Loop	0

Table 20 – Station Parking by Line Group

To account for this properly, we will either need to improve our measure of parking to include some measure of the overall parking supply in the area, or, introduce capacity constraints on train station parking supply.

4.1.3.4.3   Trip Length

A comparison has been made of VISTA07 and Zenith mode shares by trip length. Again, this analysis has been conducted by applying the Zenith Mode Choice model to the trips made by the survey respondents.

<u>Public Transport</u>

Figure 27 presents a comparison of public transport mode shares by trip length.

The solid lines represent mode share, while the dotted lines represent the number of public transport trips.

It is observable that public transport mode shares generally increase with trip length of up to approximately 30km, beyond which the mode share stabilises at approximately 20-25%.

Most public transport trips are between 5 and 25 kilometres, with the number of trips declining as trip lengths increase further.   This introduces some uncertainty in the estimates of mode share, as indicated by the widening error bars.
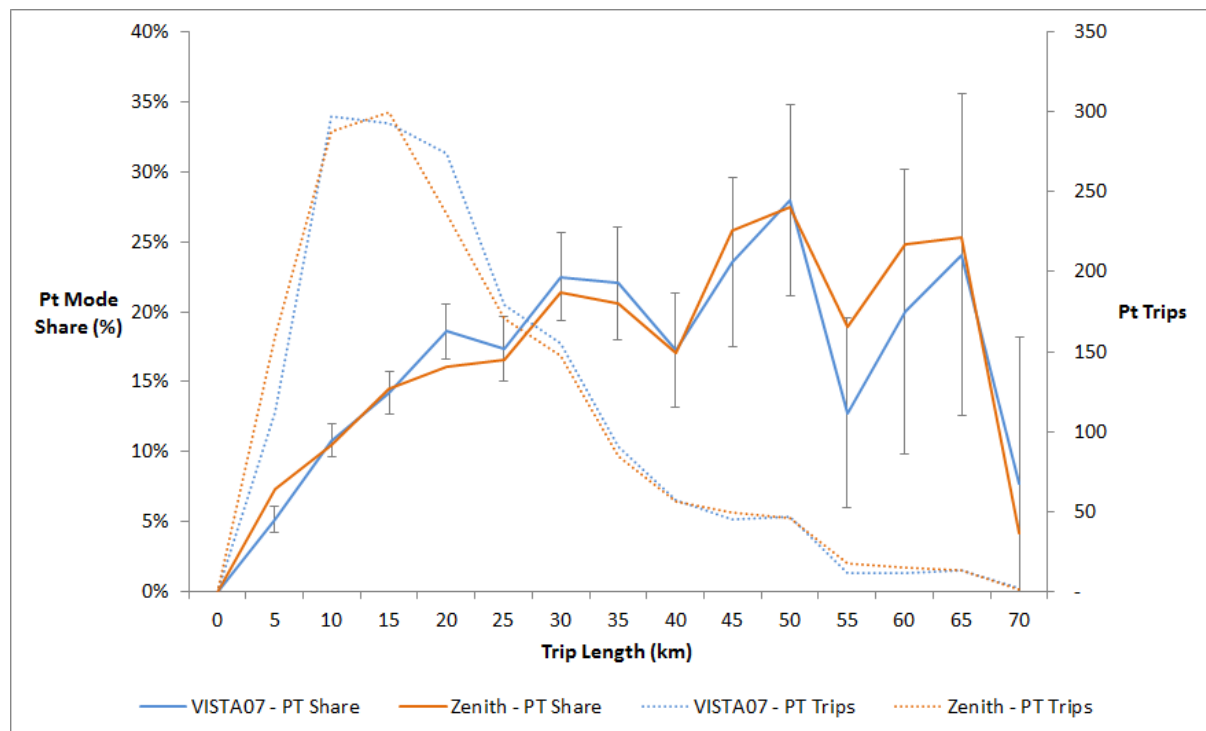

Figure 27 - Public Transport Mode Share by Trip Length (HBW)

The Zenith model appears to be doing a good job of predicting public transport mode share at a variety of trip lengths. There are, however, some minor differences:

- The model appears to slightly over-predict public transport trips in the 0 - 5km range,
- The model appears to slightly under-predict for trips in the 15 – 35km range.

To further explore these issues we have split demand by access mode (car or walk). A comparison of walk and car access mode shares is presented in Figure 28 and Figure 29 below. For both access modes the model over-predicts public transport demands in the 0 – 5km range. The model then under-predicts walk access demands in the 5 - 20k range, and then over-predicts thereafter.

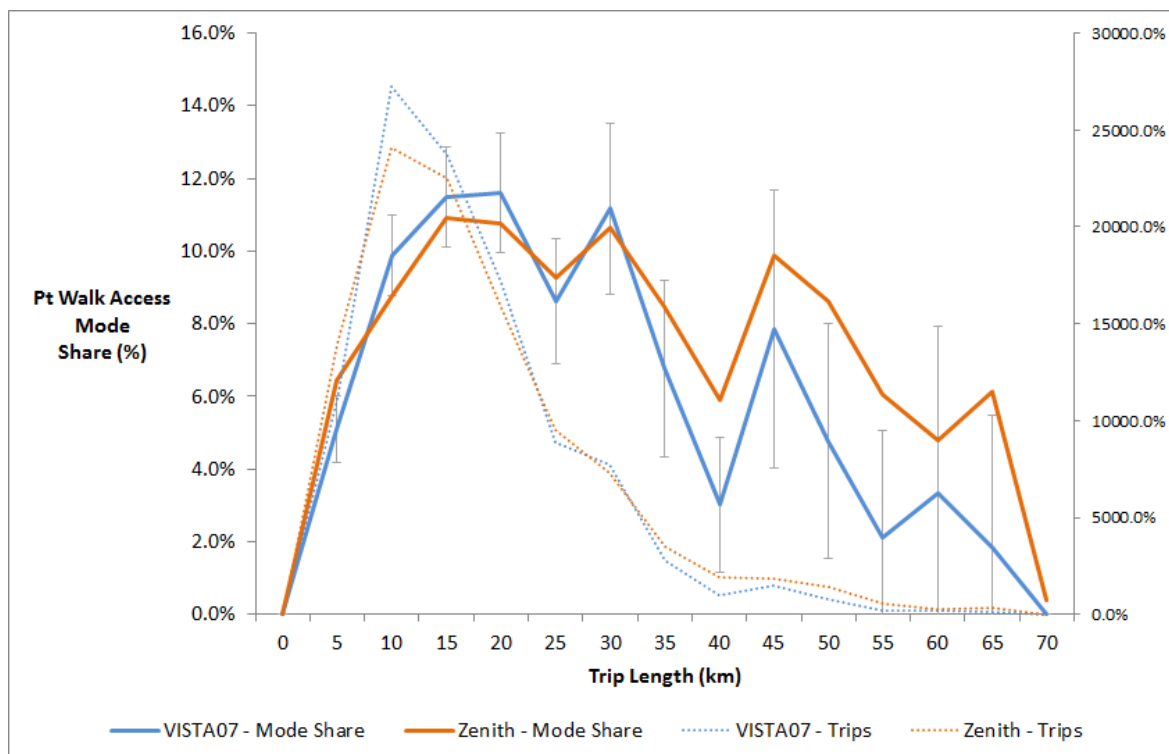By contrast, car access demands are generally under-predicted for all trip lengths above 15km.

Figure 28 - Mode Share for Walk Access to Public Transport (HBW)
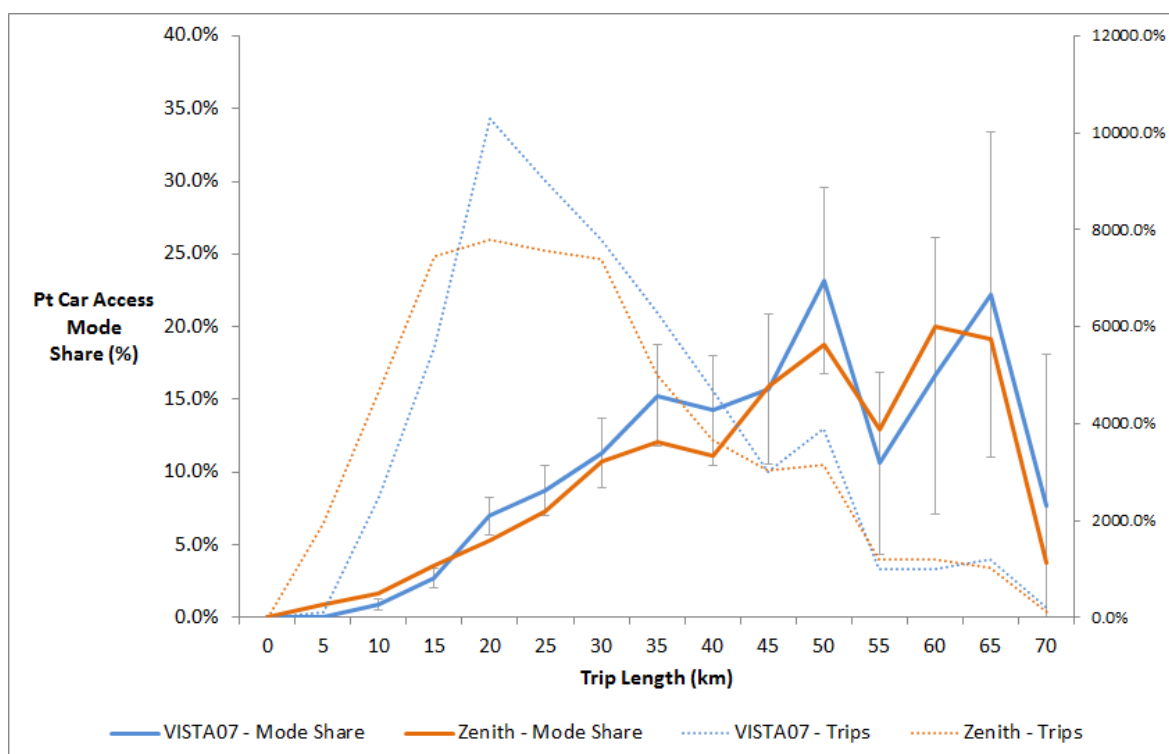

Figure 29 - Mode Share for Car Access to Public Transport (HBW)

Our current theory surrounding the car access result is that train station parking supply is not properly being taken account of (see the previous Section).

This may be upsetting the choice between walk and car access more generally, causing the differences observed for walk access. We think it likely that both access modes will improve through the properly modelling of station parking supply.

Car

Car mode shares by trip length are presented in Figure 30 below. Car mode shares tend to remain fairly stable over all trip trips, though there is a noticeable decline between 10 and 50km, from 85% to 72%. Car mode shares then appear to increase again beyond 50km.
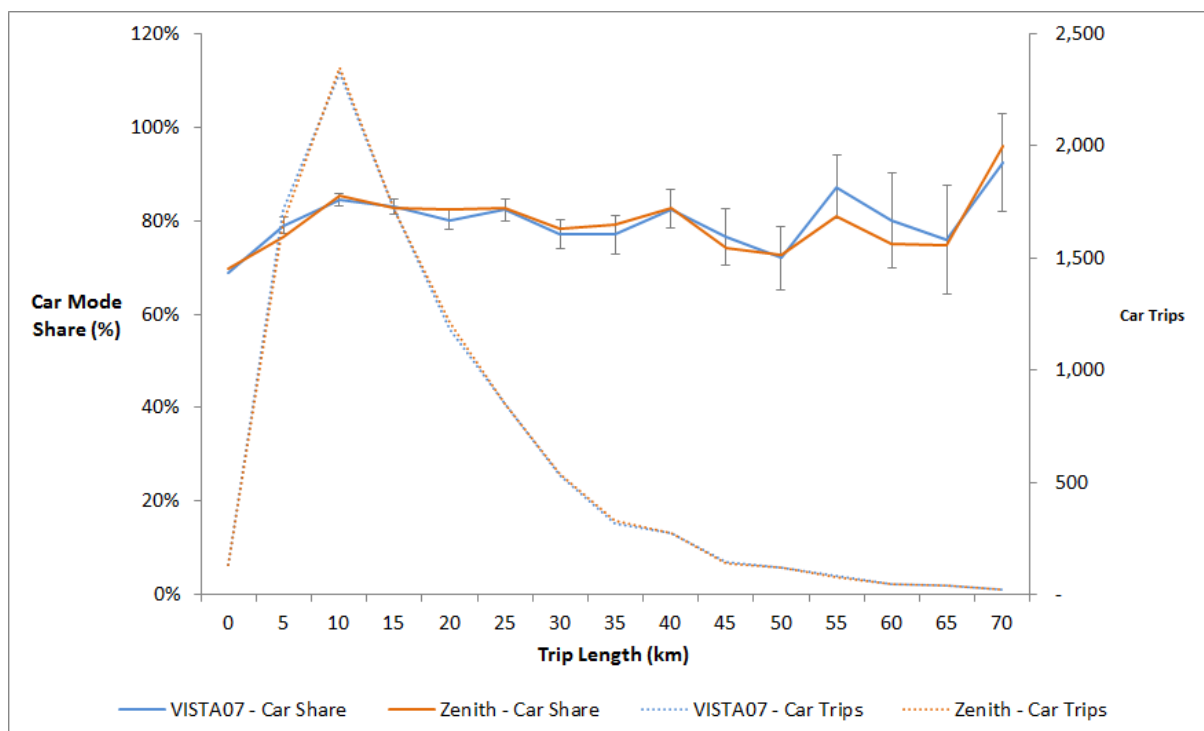

Figure 30 - Car Mode Shares by Trip Length (HBW)

The model accurately reflects this pattern, though with very slight under-prediction in the 0-5km range and over-prediction between 15 and 35km. This is (as expected), the exact opposite of what we observed for public transport.

Walking

A comparison of walking mode shares by trip length is presented in Figure 31 below. It can be observed that the model slightly under-predicts in the range 0-1km, slightly over-predicts for 2-3km, and is generally spot on for all other trip lengths. Note that the 0 km category actually represents intrazonal trips, 1km represents 0-1km, and so on.
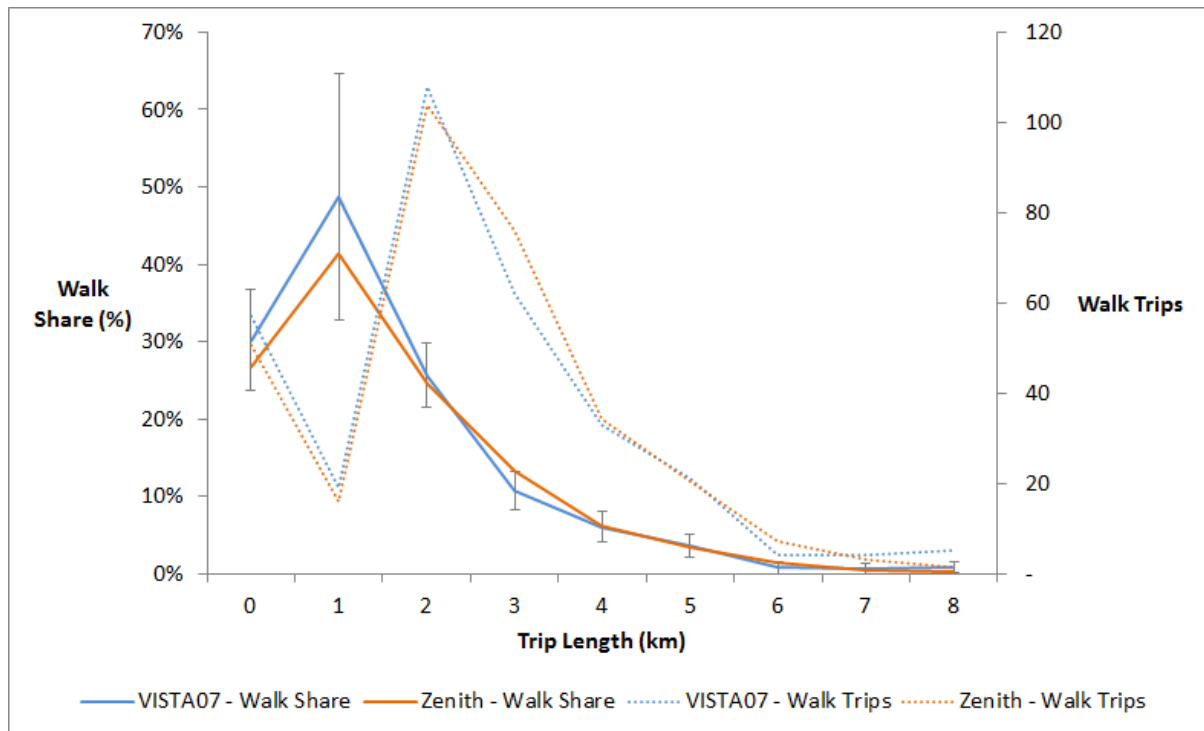
Figure 31 - Walking Mode Shares by Trip Length (HBW)

Cycling

A comparison of cycling mode shares is presented in Figure 32 below. It can be observed that the model over-predicts cycling intrazonals (0 km), and under-predicts cycling for trips less than 2km. This is the opposite to the pattern observed for walking. It appears that a closer examination of mode shares for intrazonals may result in an improved walk / cycle model (the error in the intrazonal may be biasing mode shares at other distances).

Beyond 2km, the model appears to perform quite well, given the lack of sample for cycling trips.
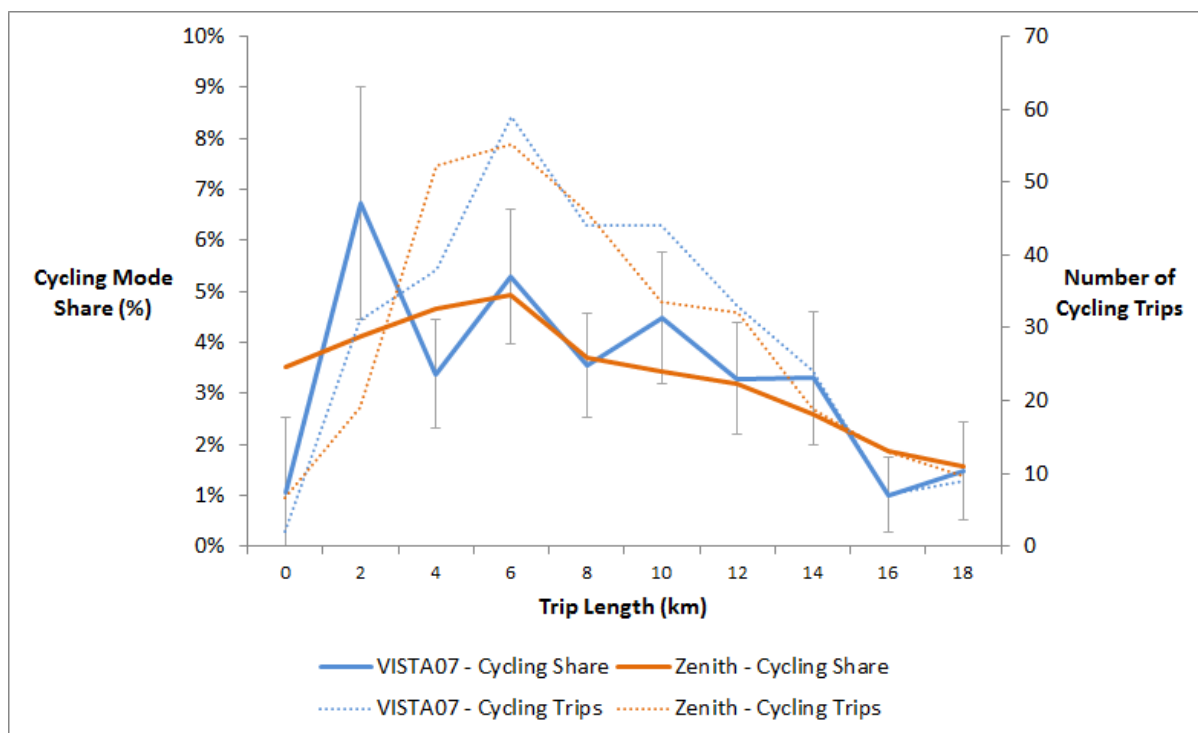
Figure 32 - Cycling Mode Shares by Trip Length (HBW)

5 Adopted Model Parameters

In Section 4 we described in detail the results of our statistical estimation of model parameters.

In a few cases we observed unexpected model parameters. In particular, the parameters for waiting time, bus in-vehicle time, and fare were lower than expected. In each case we hypothesised about why the statistical estimation process might produce unexpected results. In general, these hypotheses fall into 3 categories, which are described below, together with examples of how they might be influencing our unexpected parameter estimates:

- *Errors in our construction of the attributes of travel alternatives*
    - *Waiting time -* we think that the low parameter on waiting time is at least partly due to the model's over-estimation of waiting times for commuter travel. The model assumes that commuters wait (on average) "half the headway", given the combined frequency of sensible services. This assumption is based on the assumption that passengers arrive randomly at the stop, irrespective of the timetable. We believe, however, that commuters will generally have some knowledge of the timetable, and will time their arrival to minimise their waiting time, while simultaneously minimising the risk that they arrive too late and miss their target service. We believe that the statistical estimation process is "compensating" for the model's over-estimation of waiting times by lowering the *parameter* applied to waiting times.
    - *Fares –* estimating the fare paid for a public transport journey is not a simple matter. Several ticket types (eg. Daily, Weekly, etc) are available, at different price levels. In constructing an estimated average payable fare for each journey, we have made assumptions about the probability of each ticket type being used. At the time of writing, these probabilities have not been based on actual ticket data. As a result, our estimates of fares may be inaccurate.
- *Errors in model structure*
    - *Bus in-vehicle time –* models are by definition a simplification of reality, so errors in model structure will always be present. We can, however, attempt to limit or remove such errors by improving the structure of our model. In the case of bus in-vehicle time, we have hypothesised that variation exists in the perception of busses across the community. We have hypothesised that some people do not even consider bus as an a travel alternative, irrespective of its travel time; in a modelling sense, such people would have a large negative constant on the utility of bus, but would have a negligible value on bus in-vehicle time (as it is not taken into account). The model, however, only supports one constant for bus, and one parameter for bus in-vehicle time. We have suggested that the unexpectedly low bus in-vehicle weight might be due to the averaging of perceptions across the community.
- *Errors, biases, or lack of sample, in VISTA07 –* we have not directly attributed any of our unexpected results to this category, though it cannot be ruled out.

While these hypotheses may potentially explain the estimated parameters, more work is required to support and confirm them. Until that work takes place, we are reluctant to use such parameters without alteration, and will override them with values that fall closer to expectations.

The adopted model parameters are presented in Table 21 below.

Parameter	Parameter Estimate	Adopted Parameter	Comment
Waiting time (mins)	-0.0148	-0.0400	Increased, but still lower than in-vehicle time, to reflect that for HBW, commuters are likely wait (on average) less than half the headway
Travel time - bus (mins)	-0.0245	-0.0720	Set equal to the value of time for rail.
Fare (cents)	-0.0001	-0.0029	Assumes a value of time of $12/hr wrt. fare

Table 21 - Altered Model Parameters

In order to maintain correct overall mode shares, the constants to the model will also need to be altered. This will take place as part of a "calibration" step which will take place following the estimation of the Destination Choice model, and will involve comparing the model's predicted transit demands with other sources of observed data, such as estimated rail station boardings, the Rail OD survey, the Tram OD survey, and estimated bus route boardings.

The updated constants will be included in this report following the completion of the calibration step.