Zenith Model of Victoria

Technical Note 3
Home Based Trip Productions

Zenith Version: 2.0.0

VEITCH LISTER CONSULTING PTY LTD

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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 third 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 Aim and Scope of This Document

The primary focus of this document relates to the first step in the four-step travel modelling process: *trip generation.* This step addresses the travel choice question: how many trips will be made, and for what purpose? The scope of this note is restricted to home based trip productions. Non-home based trip productions are presented in Working Paper 4.

The remainder of this document is structured as follows:

- Section 2 describes the sources of data which have been used to develop, estimate, calibrate and validate the model,

- Section 3 describes the scope of the model,

- Section 4 describes the methodology,

- Section 5 describes the estimation and validation of the model, and

- Section 6 describes correction factors which have been included to account for under-reporting in VISTA.

2   Data Sources

Various data sources have contributed to the recalibration of the Trip Generation model.

The primary source of trip generation data was the Victorian Integrated Survey of Travel and Activity 2007 (VISTA07). Version 1.3 of the 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 trip generation, travel made by residents living outside of the Zenith model area (specifically, in Shepparton and the LaTrobe Valley), and travel made on weekends and during school and public holidays did not form part of the estimation sample. In addition, the sample was necessarily restricted to fully the set of fully responding households. That leaves a sample of 7,228 households (42% of the total sample); still a very healthy sample from which to calibrate a model.

A number of secondary data sources have also been used to validate the VISTA survey. These have included Screenline Traffic counts, Rail and Tram OD surveys, and Bus ticket validations. In *Working Paper 2: Analysis of VISTA*, we reported that VISTA under-reports travel when compared to these other data sources.

As such, it has become necessary to incorporate correction factors to scale up the trip rates estimated using VISTA.

3 Model Scope

This chapter describes the scope of the Zenith Trip Generation model in terms of:

- The set of trip purposes,
- The chosen set of household / person variables which act as predictors of trip making,
- The definition of the "modelled day",
- The spatial boundary of the model.

3.1 Trip Purposes

The Trip Generation model separately estimates travel for a wide range of distinct trip purposes.

The Zenith model includes trip purposes relating to:

- Travel made by residents
- Travel made by overseas visitors, Australian visitors and persons living outside the region
- Commercial vehicles (freight)

This note will concern itself only with the first item: *travel made by residents*, as the VISTA07 survey only includes travel made by residents.

Travel made by overseas visitors, Australian visitors and commercial vehicle traffic will be reviewed at a later date.

The resident trip purposes in the Zenith model are:

Home Based

- Home based work (white collar)
- Home based work (blue collar)
- Home based education (primary)
- Home based education (secondary)
- Home based education (tertiary)
- Home based shopping / personal business   [Home based shopping, for short]
- Home based recreation / social   [Home based recreation, for short]
- Home based serve passenger / other   [Home based other, for short]

Non-home based
- Work based work
- Work based shopping
- Work based other
- Shopping based shopping
- Shopping based other
- Other non-home based

The scope of this note is confined to the home based trip purposes.

3.2 Demographic Variables

The Zenith model currently describes households according to 7 characteristics:

- Household size
- Number of white collar workers
- Number of blue collar workers
- Number of dependants aged 0 to 17
- Number of dependants aged 18 to 64
- Number of dependants aged 65 and over
- Number of cars (excludes motor cycles)

Note that the person categories (white collar worker, blue collar worker, dependant aged 0 to 17, dependant aged 18 to 64 and dependant aged 65 and over) are mutually exclusive. A person cannot be both a dependant and a worker.

During the course of the recalibration project, an alternative classification has been explored. This classification replaces the aforementioned worker and dependant categories with:

- Full time white collar
- Part time white collar
- Full time blue collar
- Part time blue collar
- Not yet at school
- Primary school
- Secondary school
- Full time tertiary
- Part time tertiary
- Home duties
- Unemployed
- Retired

We intend at a later date to explore a further breakdown of white collar into "with tie, and without tie" in collaboration with DOT.

3.3   Definition of the Modelled Day

The Zenith Trip Generation model predicts daily travel for an average weekday during school term time, and excluding public holidays.

Under this definition, the modelled average weekday will include some university holidays.

The definition of school holiday periods can be a bit blurred, given that not all schools take holidays concurrently. In particular, holiday periods for secondary schools tend to vary.

The holiday periods of 10 private schools were examined, and the school term time was defined to encompass most schools.

This analysis is included in Appendix A, together with the adopted school term time definition.

3.4   Geographic Scope of the Model

The geographic coverage of the model is shown in Figure 1 below. The model includes all Melbourne, Geelong, Ballarat and Bendigo. The Zenith Trip Generation model has been constrained to predicting travel for residents of these areas.
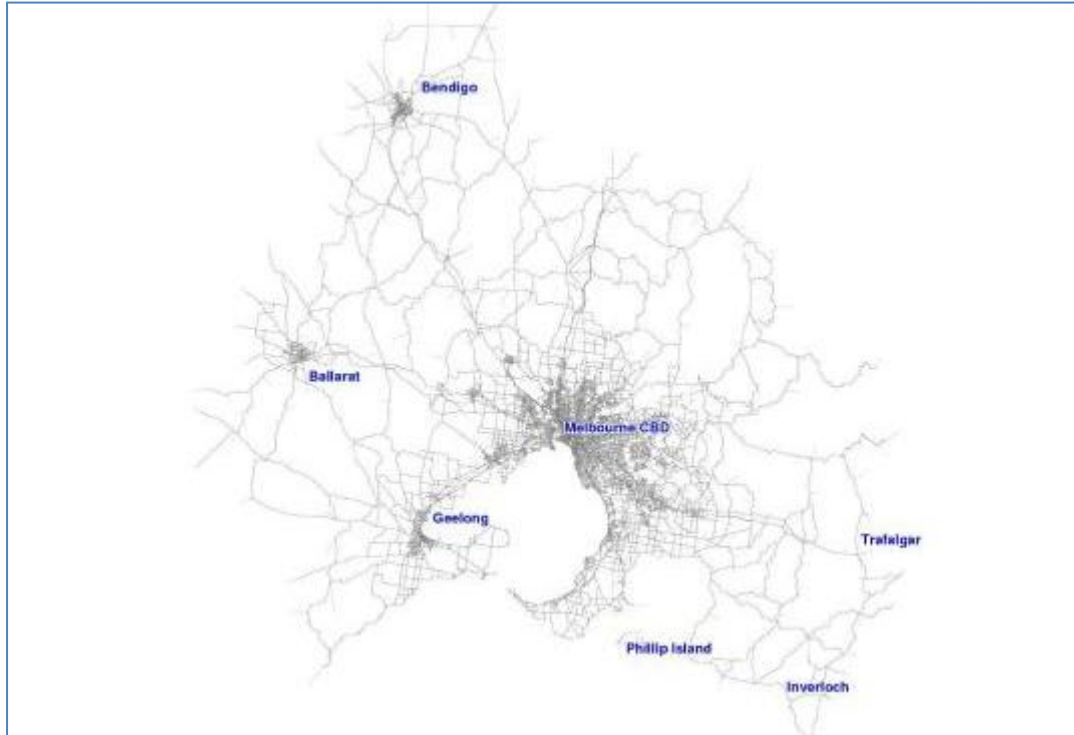
Figure 1- The Geographic Coverage of the Zenith Model

4 Methodology

4.1 Household, Person and Trip Weighting

Household, person and trip weights play an important role in the estimation and validation of the Trip Generation model.

Household and person weights aim to correct for spatial and demographic biases in the sample.

Trip weights aim to correct for some types of systematic under reporting of travel; specifically, under reporting caused by proxy reporting, and delays between the respondent's travel day, and the day on which the survey forms were completed.

For household based models, the household weights are used as weights to the regression; in other words, household types which are under-represented in the survey will be assigned a greater weight, and vice versa. For person based models, the person weight was used.

TUTI has developed household and person weights which were supplied to VLC. For the purposes of deriving its Trip Generation model, VLC has calculated an alternative set of household weights by taking the average of the TUTI person weights for each household. This has the advantage of correcting for biases in age and gender (the TUTI derived household weights currently do not).

TUTI do supply an alternative set of trip weights, which correct for under-reporting related to "proxy survey completion" and delays between the survey travel day, and the day on which the survey form was actually completed. However, these have not been used by VLC – instead, we have derived our own correction factors based on our analysis of VISTA07 (reported in *Working Paper 2 – Analysis of VISTA*).

4.2 Model Forms

As part of the development of the Zenith Trip Generation model, three different model forms have been tested. Note that only the first of these structures has been included in this document. The latter two structures do provide some interesting opportunities to improve the model, but would require a wider range of variables as input. We need to be sure that these variables can be forecast by the relevant planning authorities and / or consultants before we migrate the model to this form.

Nonetheless, all three model forms are described here for completeness.

While these models vary according to their independent variables, they all share two key similarities:

- All of the tested models are predictors of *average* trip frequencies for households of different types, rather than predictors of the trip frequency *distribution*. For example, rather than predicting the number of households who will make 0, 1, 2, 3, 4, ... etc home based shopping trips, we seek only to predict the average number of trips. This is appropriate given that the Zenith model is currently an aggregate, trip based model; when the Zenith model is re-developed as a disaggregate, tour based model (see the Zenith Development Plan), we will attempt to predict the frequency distribution,
- None of the tested models require a cross-classification of household or person attributes in their application (as they are all linear models). For example, in their application, the models may take as input the number of households with 0, 1, 2, or 3+ white collar workers, and the

number of households with 0, 1, 2, 3+ cars, but they do not require a cross-classification of these variables (for example, the number of households with 0 white collar workers *and* 0 cars). This assumption simplifies the model (specifically, it avoids the implementation of a population synthesis model), but it also limits the accuracy of the model, as interactions between variables cannot be captured. A population synthesis model is expected to be implemented as part of the implementation of a disaggregate, tour / activity based model in the future.

Each of the tested model forms is now described.

4.2.1 Current Zenith Model

The model form employed by the current Zenith model is a household based model, which classifies household members according to five person types, and the level of car ownership. The five person types are:

1. White collar workers
2. Blue collar workers
3. Dependants – aged 0 to 17
4. Dependants – aged 18 to 64
5. Dependants – aged 65 and over

Mathematically, each discrete level of each variable is expressed as a dummy variable (taking the value of 1 if that level accurately describes the household, and 0 if it does not). The variable levels included in the model are listed in Table 1 below.

Variable	Levels
Household size	1, 2, 3, 4, 5, 6+
Number of white collar workers	0, 1, 2, 3+
Number of blue collar workers	0, 1, 2, 3+
Number of dependants aged 0 to 17	0, 1, 2, 3+
Number of dependants aged 18 to 64	0, 1, 2, 3+
Number of dependants aged 65 and over	0, 1, 2+
Number of cars (excludes motor cycles)	0, 1, 2, 3+

Table 1 - Explanatory variables and their discrete levels

<u>Example</u>

A family with four members, comprising 1 white collar worker, 0 blue collar workers, 2 dependants aged 0 to 17, 1 dependant 18 to 64, and 0 dependants aged 65 and over, and owning 2 cars would be defined as follows:

	Household size						White Collar Workers				Blue Collar Workers				Dependants (aged 0 to 17)				Dependants (aged 18 to 64)				Dependants (aged 65+)			Cars			
Dummy Variable	1	2	3	4	5	6+	0	1	2	3+	0	1	2	3+	0	1	2	3+	0	1	2	3+	0	1	2+	0	1	2	3+
Household 1	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	1	0

The bottom row contains the values of the dummy variables for our example household.

In the Trip Generation model, each dummy variable has a parameter associated with it for a given trip purpose (many parameters will be 0). For example, in the current Zenith model, the following parameters are defined (as being non-zero) for Home Based Work – White Collar trips.

Attribute	Level	Parameter
White Collar Workers	1	1.0901
	2	2.0029
	3	3.1713
Dependants 0-17	0	0.1095
Cars	3+	0.1335

Table 2 - Parameter Values for the Home Based Work - White Collar, in the current Zenith model

To calculate the predicted Home Based Work – White Collar trips, we multiply (and then sum) the dummy variable parameters by the value of each dummy variable (0 or 1). For the example household described above, we have:

$$Trips = (1.0901 \times \mathbf{1}) + (2.0029 \times 0) + (3.1713 \times 0) + (0.1095 \times 0) + (0.1335 \times 0)$$

$$Trips = 1.0901$$

Strengths

The current model structure has a number of advantages:

As a predictor of trip making,

- The use of dummy variables means that the model is non-linear in the level of each household variable. For example, there is no requirement for a household with two workers to make twice the number of trips as a household with one worker. This is particularly advantageous in the case of activities which are to some degree shared across household members, such as shopping, or dropping a household member off,
- Being a household based model, the average interaction between household members can be taken into account. For example, the presence of dependent children in a household can dramatically affect the trip making of the adults in the household (in terms of chauffeuring, etc).

In application,

- The number of demographic variables which needs to be forecast is relatively limited
- The model is linear, and so there is it can be applied with no cross-classification of household variables. This obviates the need for a population synthesis model.

Weaknesses

As a predictor of trip making,

- Certain types of household interactions cannot be explicitly modelled; in particular, interactions that require two person types to be simultaneously present (for example, we cannot consider the combined effect of having a dependent child *and* a dependent adult in the household. We can only consider their effects separately.

4.2.2 Main Activity, Person Based Model

The "Main Activity, Person Based" model classifies individuals according to 12 person types:

1. Full time white collar worker
2. Part time white collar worker
3. Full time blue collar worker
4. Part time blue collar worker
5. Unemployed
6. Not yet at school
7. Primary school
8. Secondary school
9. Full time tertiary
10. Part time tertiary
11. Home duties
12. Retired

For each trip purpose, an average trip rate is estimated for each person type.

For example, for Home Based Work – White Collar, full time white collar workers have an average trip rate of 1.40 per day, while part time white collar workers have an average trip rate of 0.81 per day.

Strengths

As a predictor of trip making,
- The key feature of this model is that its representation of each person is tied to the main activity undertaken by that person. It follows logically that such a representation will be a good predictor of the types of trips made by each person. In contrast to the current Zenith model, workers are divided into full and part time, and dependants are classified by their activities, rather than age groupings, which are merely proxies for activities (e.g. 0-17 is a proxy for primary / secondary, 65+ is a proxy for retired, and 18-64 is a proxy for everyone else).

Weaknesses

As a predictor of trip making,
- No interactions between household members are taken into account
- Car ownership is ignored

In application,

- Compared with the current Zenith model, a greater number of person types (demographic variables) must be forecast for the model to be applied (12 as compared with 5).

4.2.3   Main Activity, Household Based

The "Main Activity, Household Based" model is much like the current Zenith model structure, except that the person categories (white collar worker, blue collar worker, dependant aged 0-17, dependant aged 18-64, and dependant aged 65 and over) have been substituted with the set of Main Activity.

The variable levels included in the model are listed in

Variable	Levels
Number of **full time white collar workers**	0, 1, 2+
Number of **part time white collar workers**	0, 1, 2+
Number of **full time blue collar workers**	0, 1, 2+
Number of **part time blue collar workers**	0, 1, 2+
Number of **unemployed persons**	0, 1, 2+
Number of **children not yet at school**	0, 1, 2+
Number of **primary school students**	0, 1, 2, 3+
Number of **secondary school students**	0, 1, 2, 3+
Number of **full time tertiary students**	0, 1, 2+
Number of **part time tertiary students**	0, 1+
Number of **persons engaged in home duties**	0, 1+
Number of **retired persons**	0, 1, 2+
Number of **cars (excludes motor cycles)**	0, 1, 2, 3+

Strengths

This model combines the strengths of the two previous models:

As a predictor of trip making,

- The model is non-linear in the level of each household variable
- Simple interactions between household members are taken into account
- The main activity classification offers greater explanatory power

In application,

- ▪ The model is linear, and so there is it can be applied with no cross-classification of household variables

Weaknesses

This model also combines the weaknesses of the two previous models:

As a predictor of trip making,
- ▪ The model does not consider the more complex interactions between household attributes
- ▪ The model requires the forecasting of a greater number of demographic variables.

4.3 Estimation & Validation Procedures

4.3.1 Ordinary Least Squares Regression

The model parameters have been estimated using an Ordinary Least Squares linear regression technique.

Each data point represented a household, with the independent (x) variables consisting of the household attributes, and the dependent (y) variable equal to the number of trips for the given purpose.

Separate regressions were run for each trip purpose.

The household data points were weighted to ensure that the sample was representative.

In general, all variables were included in the first attempt at model estimation. Variables were then incrementally dropped if they were found not to be statistically significant (as a rule of thumb, we have employed a 95% confidence level), and their value was not intuitive. If a parameter estimate was not statistically significant, but the value was intuitive, and consistent with other parameters, then it was generally retained.

4.3.2 Cross Validation

Given that our regression models are being developed for the purposes of *prediction* (ie. in practice, we will apply our models to all households in the modelled area), it is important to understand the predictive capabilities of the model.

To test the reliability of the model's predictions, it is preferable to apply the model to households which *were not used to estimate the model parameters.* One way to achieve this is to split the survey sample into two parts: a calibration set (used to generate model parameters), and a validation set (used to test the reliability of the model's predictions).

The ability of the model to replicate the behaviour of the validation set would be a true test of its predictive capabilities (note that the final model parameters would be estimated on the full data set).

A common limitation of this approach is a lack of sample; by splitting the sample in two, one or both of the calibration and validation sets may lack the sample size to draw robust conclusions.

An elegant solution to this limitation is to employ a single data point replacement technique.

Using this approach, the regression is run on the full sample, but with a single data point (household) excluded. The resulting model is then applied to the excluded household, to generate a single prediction. It is a prediction in the true sense of the word, as the excluded household played no part in estimating the model parameters.

This process is then repeated for each household in the sample, generating N predictions, where N is the size of the sample.

In essence, the process is equivalent to running N regressions, each on a sample of N-1 households, and each applied to a single household. Fortunately, the linearity of our regression model enables us to infer what the predicted values would have been, *without actually running the N regressions*.

VLC has employed this technique. All of the model validation results presented in later sections are based on these predicted values and are truly independent of the sample used to generate the model parameters. As such, the validation results provide a fair assessment of how the model will perform when applied to households which are not part of the survey.

4.4 Model Validation Criteria

The DOT has provided a draft copy of their document: "*Guidelines for Strategic Transport Model Development: Calibration, Reasonableness Checks, Validation and Sensitivity Testing, Sept 2010.*" In that document, the recommended criteria for model calibration and validation criteria for Trip Generation are summarised as follows:

Check	Segmentation	Desired Criteria
Compare total modelled trips to VISTA	Total Melbourne	$\pm 5\%$
	LGA	$\pm 10\%$
	Trip Purpose	$\pm 10\%$
	LGA and Trip Purpose	$\pm 15\%$
Apply trip production model to VISTA responses	Household	$R^2 \geq 0.85$

Table 3 – DOT Trip Generation Validation Criteria

NOTE: These criteria are still being developed by DOT and are subject to review.

At this stage, VLC believes that the proposed criteria should be adjusted, and as such, we haven't explicitly used the desired criteria thresholds to validate the model. We hope to discuss this with DOT in the near future.

Our reasoning is as follows:

- With VISTA only capturing a small sample of total people, there are sample size issues which need to be considered when setting a desired validation criterion. This is particularly the case as the level of disaggregation increases. For example, the average sample size for each LGA is 213 households, but not all LGAs are equally sampled; some have 500 households, while others have less than 100. It would be wrong to apply the same simplified validation criteria to all LGAs irrespective of sample size.
- Given sampling issues, the VISTA trip rates cannot be assumed to be correct. However, for any given sample, it is a simple matter to calculate a *confidence interval* for the true mean. For

example, the sampled average trip rate for the Boroondara LGA for home based shopping is 1.33, with a sample size of 265 households. Given the sample size and observed variability in the sample, we can only be 95% confident that the true trip rate (if we could somehow survey all households) lies within 17% of this value (ie. within 1.11 and 1.56). The smaller the sample, or the greater the variability in trip making within the sample, the wider the confidence interval, and the less confidence we can have in the VISTA trip rate. It is our view that validation criteria should be expressed in terms of these confidence intervals, rather than fixed percentages.

▪ It is difficult to apply the same criteria to all trip purposes. Some trip purposes (eg. commuting) are more predictable than others (eg. shopping). Most workers will undertake a work trip each day, but shopping may only be undertaken sporadically.

Given these complications, it is difficult to arrive at a set of "one size fits all" validation criteria. As such, we have not attempted to do so at this stage.

What we have attempted to do, however, is transparently illustrate the performance of the model for each trip purpose, and for a variety of demographic and spatial groups. We hope that this analysis can usefully inform the further development of validation criteria.

5   Results

5.1   Home Based Work – White Collar

5.1.1   Travel Market

This section provides a high level analysis of the market for *Home Based Work - White Collar* trips, which we will refer to as white collar work.

The Zenith model divides people into five categories:

- White Collar Workers
- Blue Collar Workers
- Dependants aged 0 to 17
- Dependants aged 18 to 64
- Dependants aged 65 and over

The breakdown of VISTA07 white collar work trips according to this classification is seen in Figure 2 below.
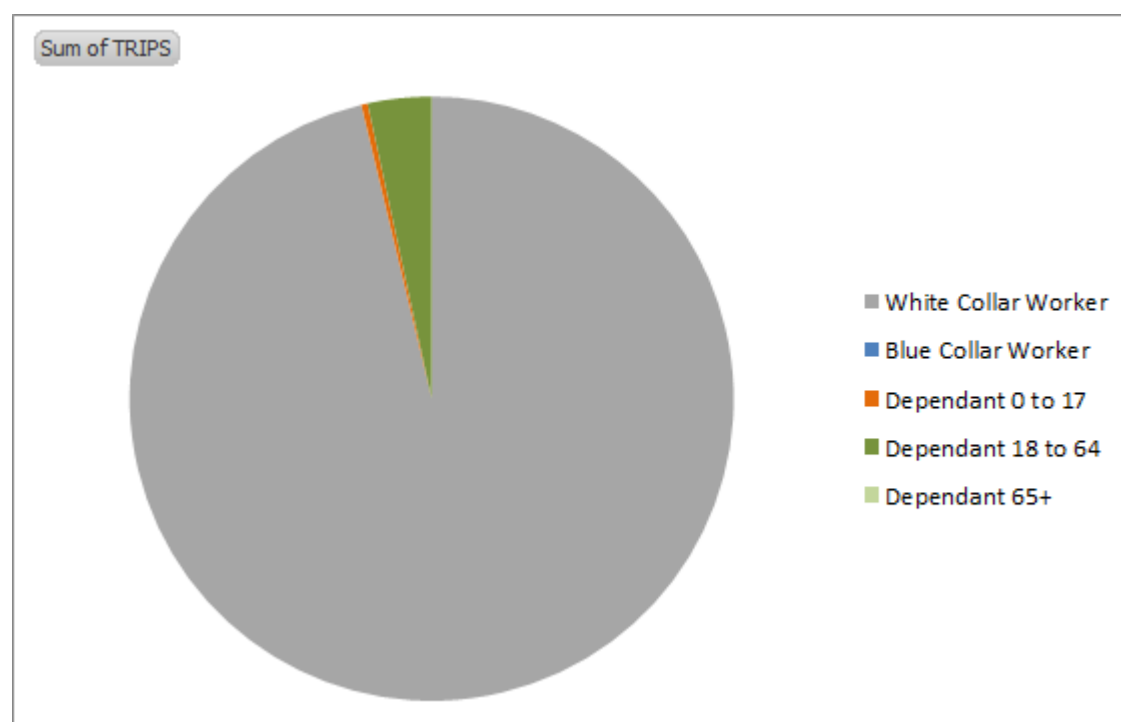
*Figure 2 - The breakdown of Home Based Work - White Collar Trips by Zenith Variables*

Over 96% of white collar work trips are made by white collar workers. The remainder are students (mostly tertiary) who also undertake some part time work.

This is clearly illustrated in Figure 3 below, which shows the breakdown of trips according to Main Activity. Full time white collar workers are responsible for 75% of trips, with an extra 21% made by part time workers, with the remainder made up by students who also work.
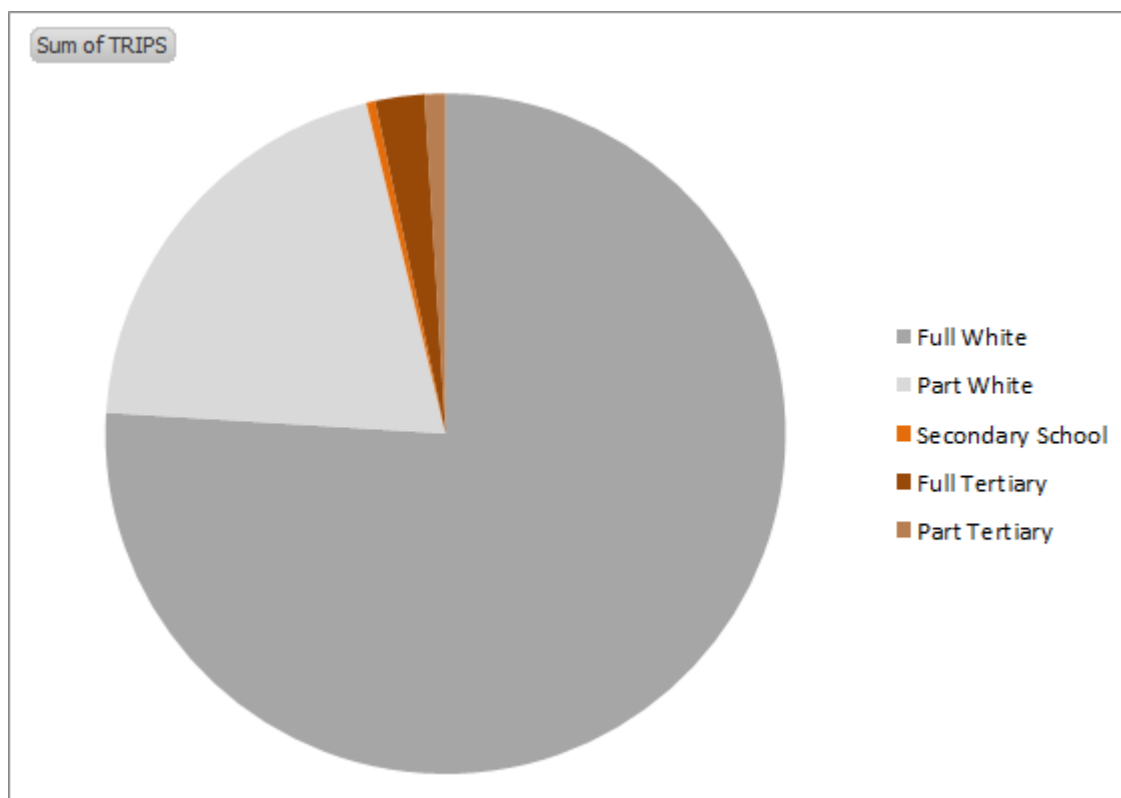
Figure 3 - The Breakdown of Home Based Work - White Collar Trips by Main Activity

The average trip rate per person for each of the Zenith person types is shown in Figure 4 below. White collar workers make approximately 1.28 home based work trips per day (equivalent to 0.64 return trips).
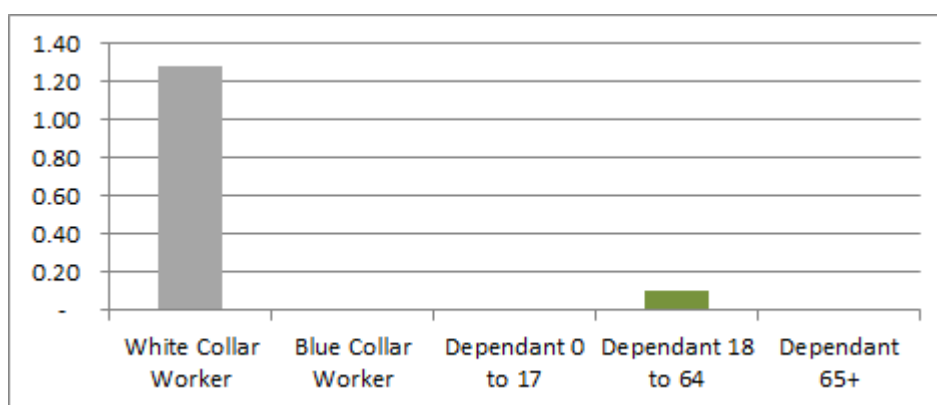
Figure 4 - Average Home Based Work – White Collar Trip Rate per Person by Zenith Variables

A more revealing analysis of trip rates is provided in Figure 5 below, which shows that full time and part time workers average 1.47, and 0.87 trips per day respectively. Interestingly, part time tertiary students average 0.41 trips per day, while full time students travel to work less frequently, at 0.32 trips per day.
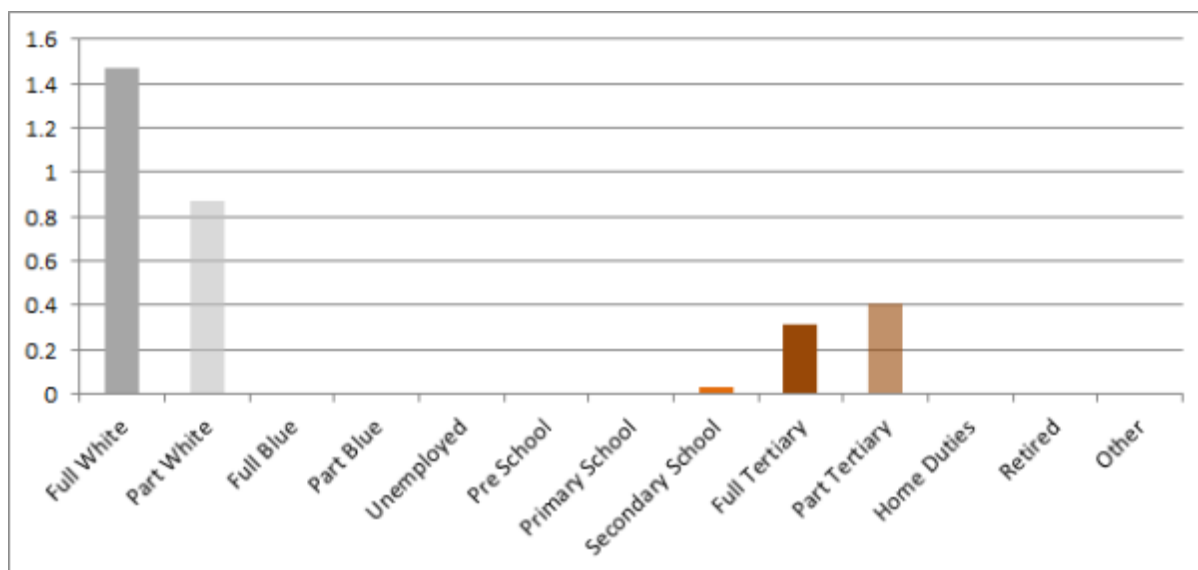
Figure 5 - Average Home Based Work - White Collar Trip Rate by Main Activity

5.1.2   Model Estimation

5.1.2.1   *Parameter Estimates*

The re-estimated model parameters for white collar work are presented in Table 4 below.

The value of the model parameter is referred to as the "Parameter Estimate", while the T-Statistic, P-Value and Standard Error report the variance properties of the parameter value.

Parameter	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE	STANDARD ERROR
WHITEWORKERS_1	1.403	39.599	0.000	0.035
WHITEWORKERS_2	2.671	63.135	0.000	0.042
WHITEWORKERS_3+	4.614	44.600	0.000	0.103
DEPS_0TO17_1+	-0.402	-10.456	0.000	0.038
DEPS_18TO64_1	0.339	8.740	0.000	0.039
DEPS_18TO64_2+	0.515	7.432	0.000	0.069
CARS_1	-0.101	-3.081	0.002	0.033
CARS_3+	0.104	1.914	0.058	0.054

Table 4 –Parameter Estimates and Properties for Home Based Work – White Collar

To help illustrate the meaning of these parameters, a household with 1 white collar worker, 1 dependant aged 18-64, and 2 dependants aged 0-17, and 1 car we simply add together all of the parameters which accurately define the household. In this case, these parameters are:

- WHITEWORKERS_1   (1.403)
- DEPS_0TO17_1+   (-0.402)
- DEPS_18TO64_2+   (0.339)
- CARS_1   (-0.101)

The sum of these parameters is:

1.403 – 0.402 + 0.339 – 0.101 = 1.239 trips per day

If the household were to have two cars instead, then we would have:

- WHITEWORKERS_1   (1.403)
- DEPS_0TO17_1+   (–0.402)
- DEPS_18TO64_2+   (0.339)

The sum of these parameters is:

1.403 – 0.402 + 0.339 = 1.34 trips per day.

This serves to illustrate that if a level of any variable is absent from the parameter list, its value is implicitly zero (eg. CARS_0, CARS_2).

As expected, the number of white collar workers in the household has the largest impact on the number of trips, with parameters of 1.403, 2.671 and 4.614 for households with 1, 2, and 3+ white collar workers respectively.

As one might also expect, the number of white collar trips appears to be approximately linear with the number of white collar workers, though the second white collar worker is less likely to make a home based work trip, suggesting that the second white collar worker is more likely to be part time or have other responsibilities. Put another way, two households, each containing 1 worker (2 x 1.403), is likely to make slightly more trips than one household with 2 workers (1 x 2.671), all other things being equal.

Interestingly, the presence of dependent children in a household has a strong negative impact on the number of white collar work trips, with a parameter of –0.402 for any household which has 1 or more dependants aged 0-17. This can be interpreted as households with children making less home based work trips, all other things being equal.

This can be explained in terms of the increased demands placed on adults caring for dependent children such as chauffeuring, shopping, and house duties such as cooking, cleaning, etc. Morris et al (2010) have shown that this burden largely falls on women (including in households where both parents work), with a noticeable movement towards part time and casual (rather than full time) work among mothers of dependent children.

Given this, the –0.402 parameter is likely to have two related causes:

- An increased propensity towards part time work (over full time work) in households with children,
- An increase in stops on the way to or from work, such as dropping the kids at school, or buying groceries. This would cause a reduction in home based work trips, and a simultaneous increase in home based shopping and home based other. Given this explanation, we should expect that the presence of dependent children will appear with a positive parameter home based shopping and other (which turns out to be the case).

The presence of a dependant adult aged 18-64 has the opposite effect; parameters of 0.338 and 0.493 are estimated for households with 1 and 2+ dependants aged 18-64, respectively. This is also likely to have two valid explanations:

- Adult dependants do make white collar work trips, with an average frequency of 0.1 per day (as illustrated in Figure 4 above),
- An adult dependant is likely to support the worker(s) of the household by taking responsibility for activities such as shopping, and chauffeuring the children to and from school. This increases the likelihood of the worker making a direct trip to or from work.

Household car ownership also has an interesting influence on the frequency of white collar work trips. Owning exactly one car has a negative impact on trip rates, relative to having no car at all (with a parameter of -0.101), as workers in one car households are more likely to drop other family members off on the way to work. Having two cars has no effect (relative to having none), while having three cars increases white collar work trips (with a parameter of 0.104).

5.1.3 Model Validation

5.1.3.1 Demographic Validation

Having estimated the parameters of the Zenith model, we have then *applied* the model to the surveyed households, to obtain a predicted number of trips for each household. These predictions were then compared with the actual number of trips recorded in the VISTA survey. The comparison was not conducted at the level of individual households; rather, households were grouped according to three demographic variables: household size, household income and household car ownership.

For example, in the first row of Table 5 below, we examine the white collar work trip rates for households of various *sizes*. The "Sample" column indicates that there were 1571 single person households in our VISTA07 sample. In VISTA these households reported an average of 0.51 white collar work trips per household. When the re-estimated Zenith model is applied to this subset of households, the model also produces an average trip rate of 0.51, suggesting that the model performs well when applied to single person households.

The 95% C.I. (95% confidence interval) of ±9% indicates that with a sample of 1571, we can be 95% confident that the *true average* for single person households lies within 9% of our sampled average (ie. between 0.46 and 0.55). By true average, we mean the average we would obtain if we could survey the entire population of single person households across the study area.

The bounds of the 95% confidence interval (in this case 0.46 and 0.55) have been indicated in the chart using *error bars*.

It can be observed that:

- The rate of white collar work trips increases as household size increases, up to four persons per household. Beyond four, the trip rate is steady at approximately 1.8, indicating that any extra people are likely to be children, rather than workers. The predictions of the model accurately replicate the pattern observed in the survey.
- Households with higher incomes make (on average) more white collar work trips. Households with higher incomes will tend to have more workers (particularly full time workers), leading to more trips. The model generally replicates the observed pattern, though there is a tendency to slightly over-predict the trips of low income households, and under-predict the trips of high income households. We believe this to be because the model does not currently differentiate between part and full time workers.

- The number of trips also increases with the number of cars owned by the household. This is a correlative relationship for the most part; the number of cars owned tends to be correlated with the number of workers. However, there is a weak causal relationship between car ownership and white collar work trip rate, as indicated by the parameter estimates in the previous section. The model is quite successful in replicating the observed pattern.
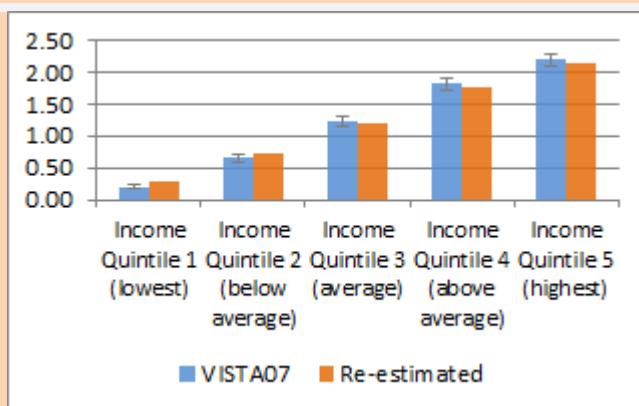
Average Household Trip Rates by Household Characteristics
## Home Based Work – White Collar | Re-estimated Zenith Model
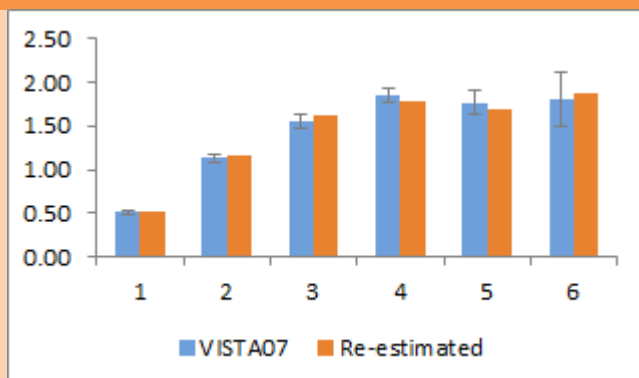
Household Size

Household Size	VISTA07	Re-estimated	Diff	95% C.I.	Sample
1	0.51	0.51	1%	± 9%	1,571
2	1.13	1.17	4%	± 5%	2,682
3	1.56	1.61	4%	± 6%	1,182
4	1.85	1.78	-4%	± 6%	1,277
5	1.76	1.70	-4%	± 12%	392
6	1.81	1.87	3%	± 21%	103

Household Income

Income Quintile	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Income Quintile 1 (lowest)	0.20	0.30	50%	± 17%	1,423
Income Quintile 2 (below average)	0.66	0.73	11%	± 9%	1,409
Income Quintile 3 (average)	1.24	1.22	-2%	± 6%	1,467
Income Quintile 4 (above average)	1.82	1.78	-3%	± 5%	1,441
Income Quintile 5 (highest)	2.20	2.16	-2%	± 5%	1,488
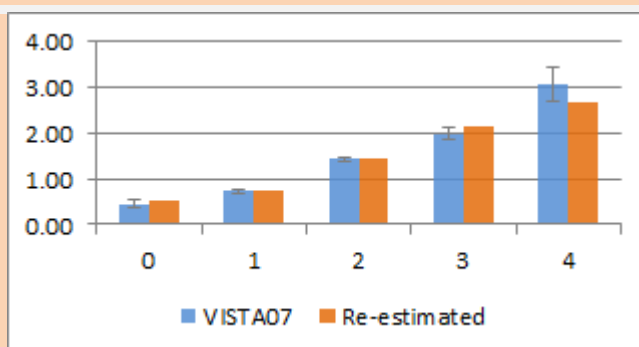
Cars Owned

Car Ownership	VISTA07	Re-estimated	Diff	95% C.I.	Sample
0	0.45	0.52	14%	± 20%	483
1	0.74	0.76	2%	± 6%	2,614
2	1.43	1.43	0%	± 4%	3,105
3	1.99	2.15	8%	± 7%	745
4	3.07	2.69	-12%	± 12%	225

Table 5 - Validation by Demographic Categories (White Collar Work)

5.1.3.2   Spatial Validation

Using an identical process to that used in the Demographic Validation, we have applied the re-estimated Zenith model to the households surveyed in VISTA07, and compared our predicted trips with the actual number of trips recorded by the survey respondents.

For the purposes of comparison we have grouped households according to their home location. We have employed three levels of spatial grouping:

- Local Government Area (LGA)
- Concentric Rings (Inner City, Inner Suburbs, Middle Suburbs, Outer Suburbs, etc)
- Statistical Division (SD)

LGA's provide a relatively localised view of trip rates (which can be highly informative), but a lack of sample size is often a problem when examining the surveyed trip rates for a single LGA.

Concentric Rings allow us to ascertain whether distance from the Central Business District affects trip rates, while SDs allow us to spot variations between Melbourne, Geelong, Bendigo and Ballarat.

For each level of grouping, we have provided three types of analyses:

- A map, which shows the VISTA07 and Zenith trip rates for each LGA
- A scatter plot which shows the correlation between VISTA07 and Zenith trip rates. The size of each point represents the sample size for the LGA, while horizontal error bars are used to indicate a 95% confidence interval on the surveyed trip rate.
- A table which presents the raw data.

Referring to the LGA analyses (Figure 6 and Table 6 below), it can be observed that:

- The trip rate generally declines as one moves further away from the CBD,
- The model generally replicates the patterns observed in the survey (demonstrated by the R-Squared of 0.7), but there is still a fair degree of uncertainty attached to the surveyed trip rate of each LGA. The modelled prediction falls within the 95% confidence interval in 31 of the 34 the LGAs (the exceptions being Greater Geelong, Mornington Peninsula and Nillumbik).
- There is a noticeable pattern of over-prediction for LGAs on the perimeter of Melbourne. Wyndham, Melton, Hume, Nillumbik, Cardinia, the Mornington Peninsula and Geelong are all over-predicted by over 10%, suggesting that accessibility to jobs may play a role in white collar work trip rates.

This pattern of over-prediction for outer suburbs is made clear by the Concentric Ring analysis (refer to Figure 7 and Table 7). It can be observed that:

- The model under-predicts trip rates by 5-10% for the Inner City and Inner Suburbs, and
- The model over-predicts trip rates for the Outer Suburbs and the Major Regional Centre (Geelong) by around 10%,
- Interestingly, the model under-estimates trip rates for Regional areas of Bendigo and Ballarat by 4%.

At the SD level, the model is accurately predicting trip rates for Melbourne overall, though this is not surprising as the regression will have been heavily weighted towards Melbourne trip rates, due to

Melbourne's relatively large population. The model tends to slightly under-estimate trip rates in both Bendigo and Ballarat, and over-estimate in Geelong as discussed previously.

These spatial differences, in particular the tendency of the model to under-predict the trips of inner suburbs, and over-predict the trips of outer suburbs, may be worth exploring at a later date.

Average Household Trip Rate by LGA
Home Based Work – White Collar | Re-estimated Zenith Model

$y = 1.0002x$
$R^2 = 0.7062$
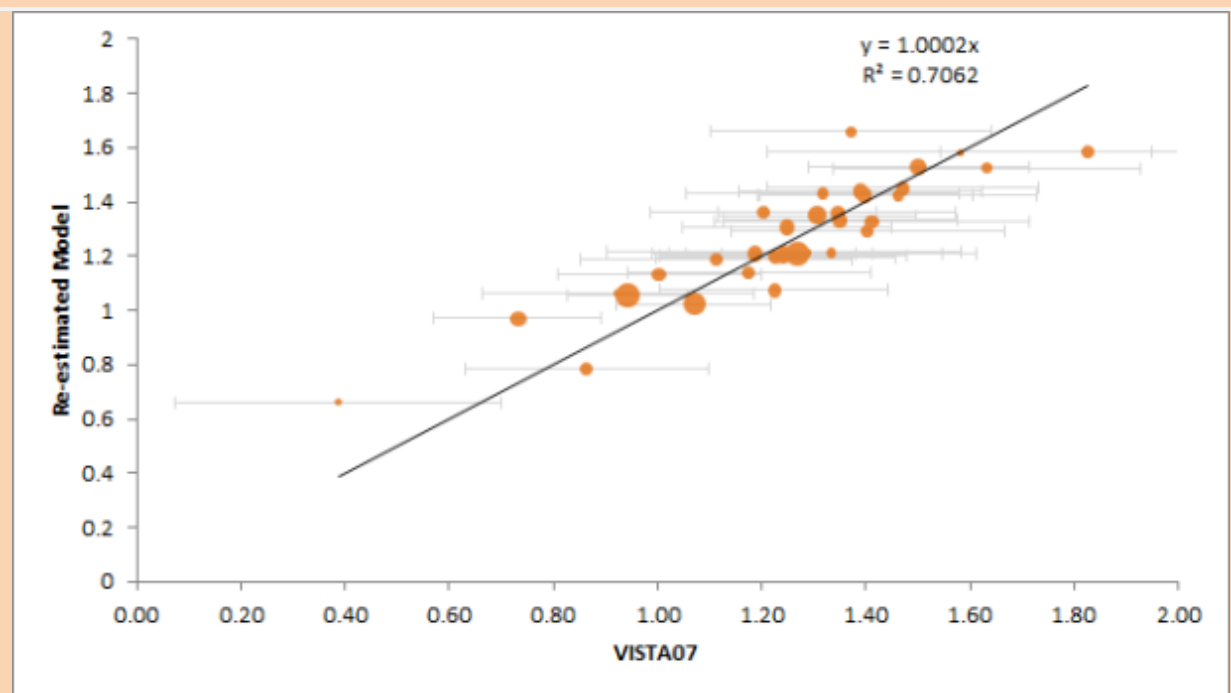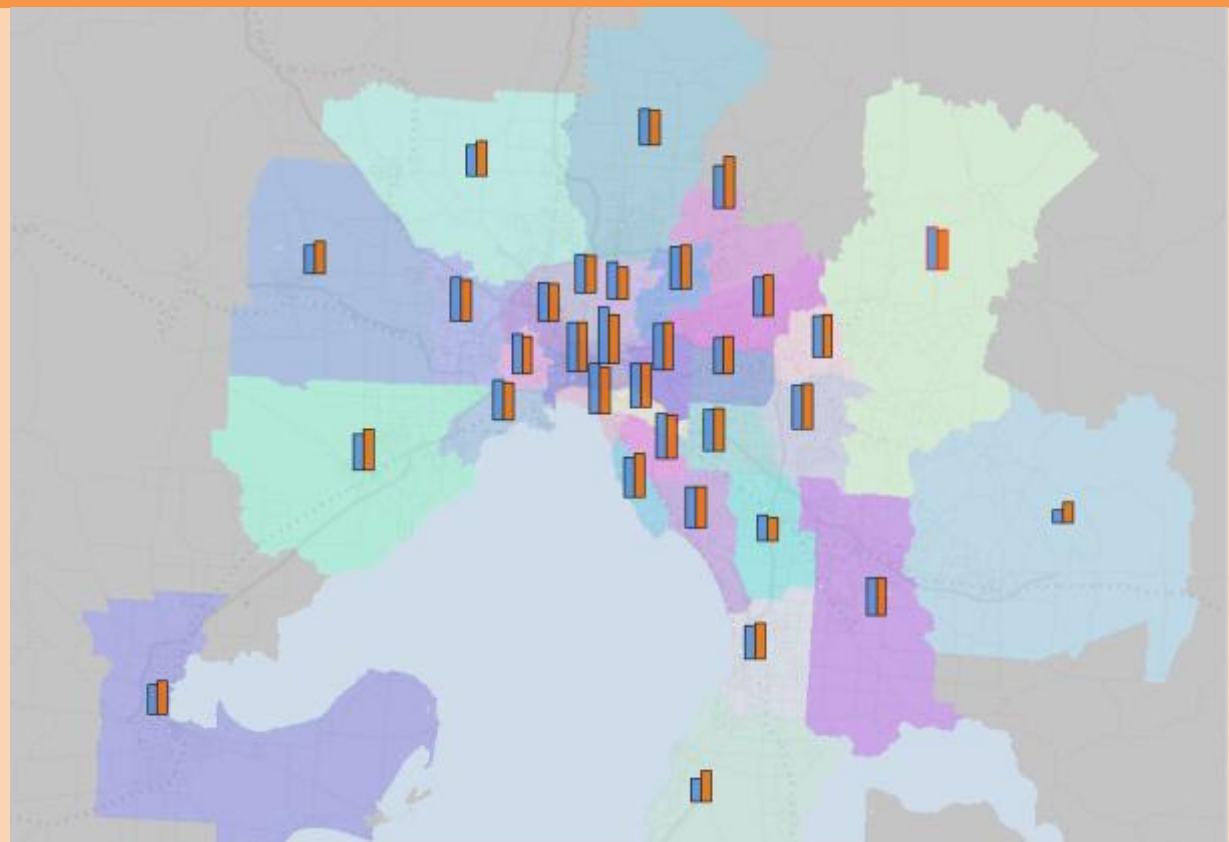
Figure 6 – Comparison of Modelled and VISTA07 Trip Rates by LGA (White Collar Work)

Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Ballarat (C)	1.27	1.21	-5%	±11%	581
Banyule (C)	1.40	1.42	2%	±15%	240
Bayside (C)	1.32	1.43	9%	±20%	153
Boroondara (C)	1.50	1.53	2%	±14%	265
Brimbank (C)	1.41	1.33	-6%	±22%	171
Cardinia (S)	0.39	0.66	71%	±81%	32
Casey (C)	1.23	1.20	-2%	±19%	220
Darebin (C)	1.22	1.07	-12%	±18%	194
Frankston (C)	1.11	1.19	7%	±23%	181
Glen Eira (C)	1.47	1.45	-1%	±18%	197
Greater Bendigo (C)	1.07	1.02	-4%	±14%	488
Greater Dandenong (C)	0.86	0.79	-9%	±27%	167
Greater Geelong (C)	0.94	1.06	12%	±12%	572
Hobsons Bay (C)	1.28	1.21	-6%	±20%	128
Hume (C)	1.00	1.13	13%	±20%	189
Kingston (C)	1.35	1.33	-1%	±17%	225
Knox (C)	1.39	1.44	4%	±17%	223
Manningham (C)	1.25	1.31	5%	±16%	242
Maribyrnong (C)	1.33	1.21	-9%	±21%	104
Maroondah (C)	1.34	1.36	1%	±17%	225
Melbourne (C)	1.58	1.58	0%	±23%	62
Melton (S)	0.92	1.06	15%	±28%	88
Monash (C)	1.31	1.35	3%	±14%	326
Moonee Valley (C)	1.24	1.22	-2%	±27%	153
Moreland (C)	1.24	1.20	-3%	±19%	239
Mornington Peninsula (S)	0.73	0.97	33%	±22%	251
Nillumbik (S)	1.37	1.66	21%	±20%	112
Port Phillip (C)	1.63	1.52	-7%	±18%	129
Stonnington (C)	1.46	1.42	-3%	±18%	146
Whitehorse (C)	1.19	1.21	2%	±17%	239
Whittlesea (C)	1.18	1.14	-3%	±20%	173
Wyndham (C)	1.20	1.36	13%	±18%	179
Yarra (C)	1.83	1.59	-13%	±15%	146
Yarra Ranges (S)	1.40	1.29	-8%	±19%	188

Table 6 - Comparison of Modelled and VISTA07 Trip Rates by LGA (White Collar Work)

Average Household Trip Rate by Region
Home Based Work – White Collar | Re-estimated Zenith Model

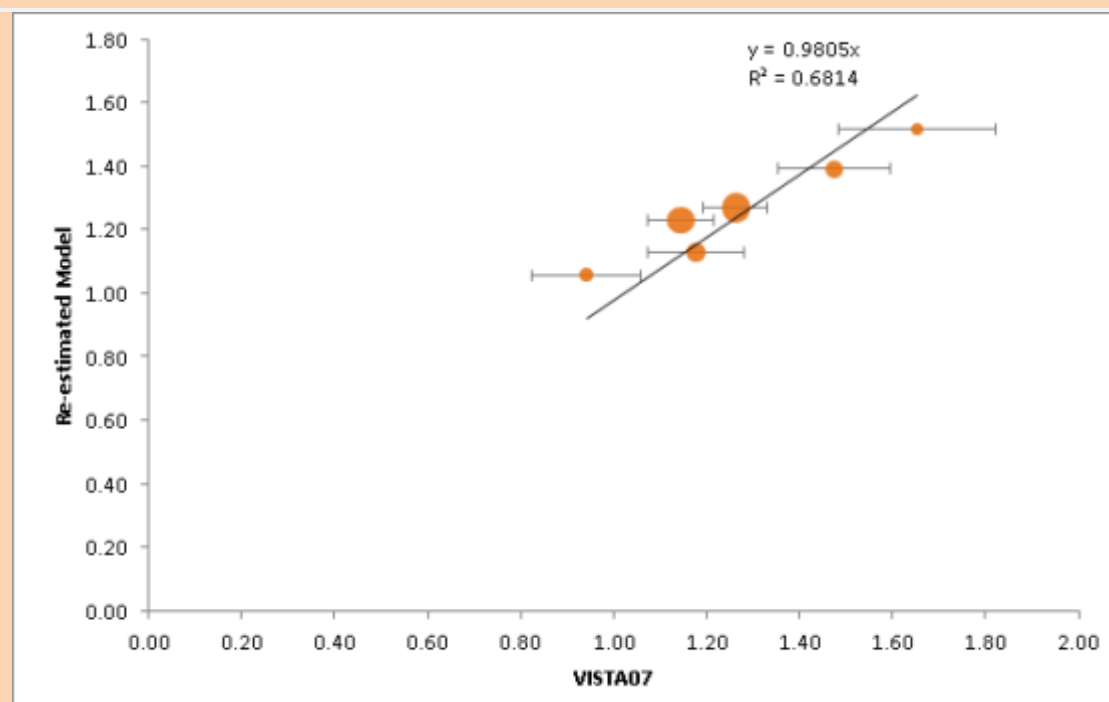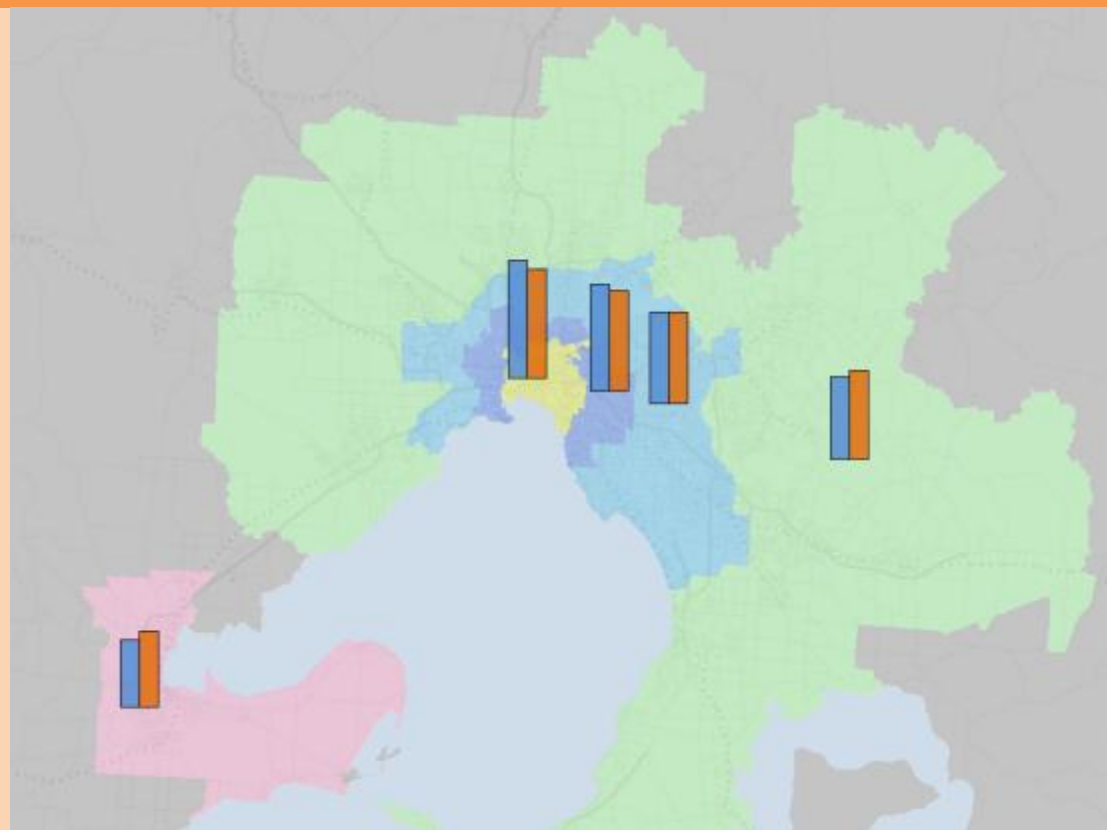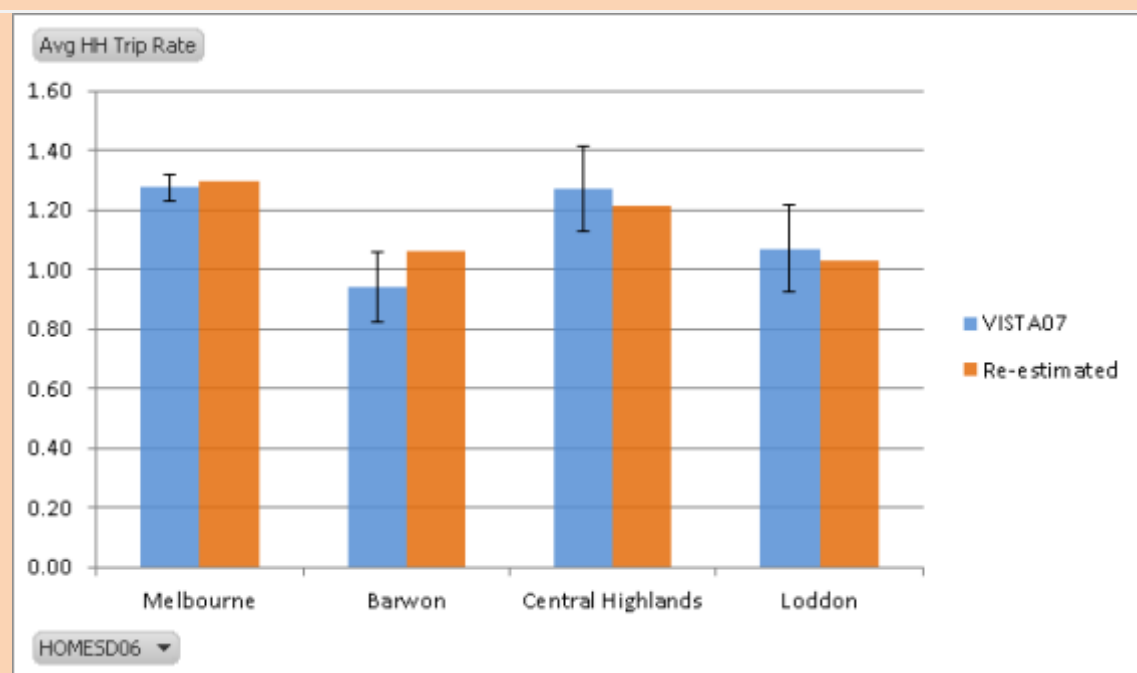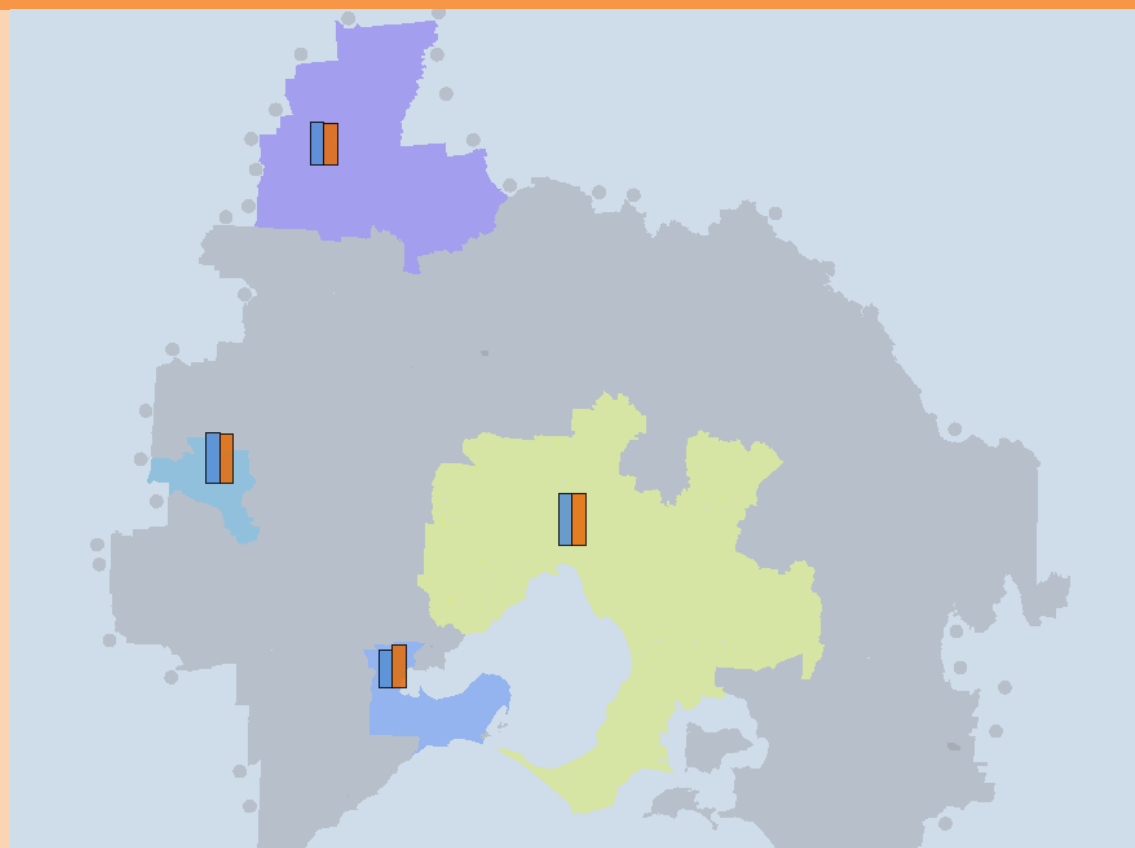*Figure 7 - Comparison of Modelled and VISTA07 Trip Rates by Region (White Collar Work)*

Avg Household Trip Rate	VISTA07	Re-estimated	Diff	95% CI	Sample
Inner City	1.65	1.52	-8%	± 10%	377
Inner Suburbs	1.47	1.39	-6%	± 8%	813
Middle Suburbs	1.26	1.27	0%	± 5%	2,328
Outer Suburbs	1.14	1.23	8%	± 6%	2,069
Major Regional Centre	0.94	1.06	12%	± 12%	572
Regional	1.18	1.13	-4%	± 9%	1,069

Table 7 - Comparison of Modelled and VISTA07 Trip Rates by Region (White Collar Work)

Average Household Trip Rate by SD
Home Based Work – White Collar | Re-estimated Zenith Model

Figure 8 - Comparison of Modelled and VISTA07 Trip Rates by SD (White Collar Work)

Avg HH Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.
Melbourne	1.28	1.29	1%	±3%
Barwon	0.94	1.06	12%	±12%
Central Highlands	1.27	1.21	-5%	±11%
Loddon	1.07	1.02	-4%	±14%

Table 8 - Comparison of Modelled and VISTA07 Trip Rates by SD (White Collar Work)
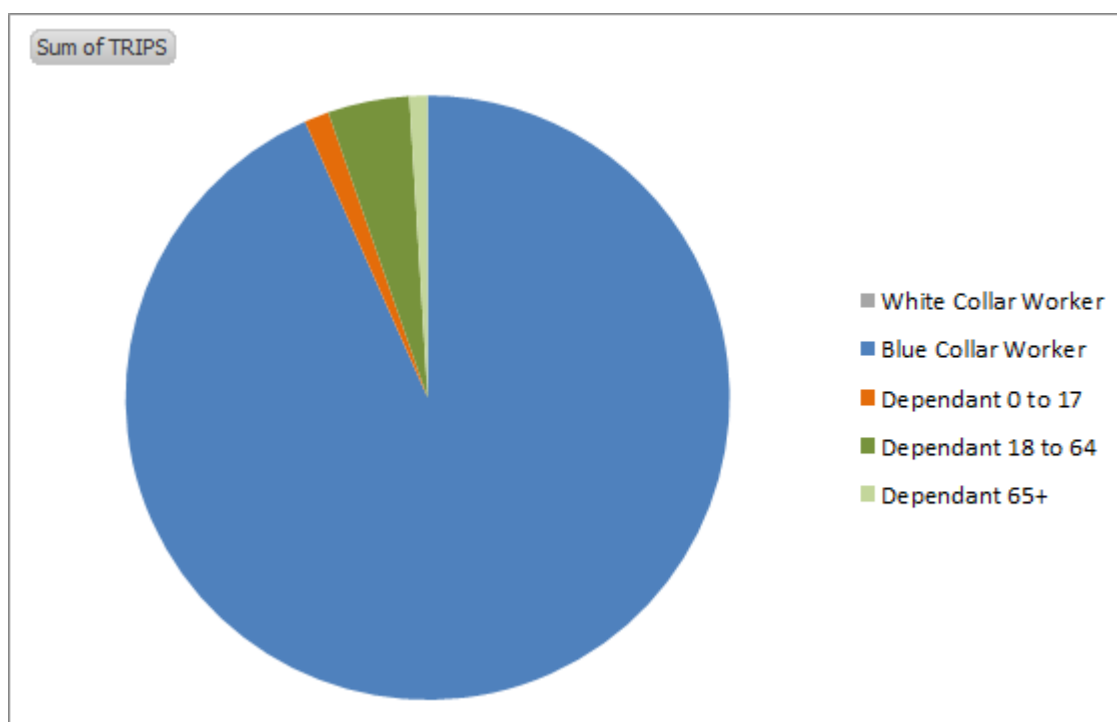
5.2   Home Based Work – Blue Collar

5.2.1   Travel Market

This section provides a high level analysis of the market for *Home Based Work – Blue Collar* trips, which we will refer to as Blue Collar Work.
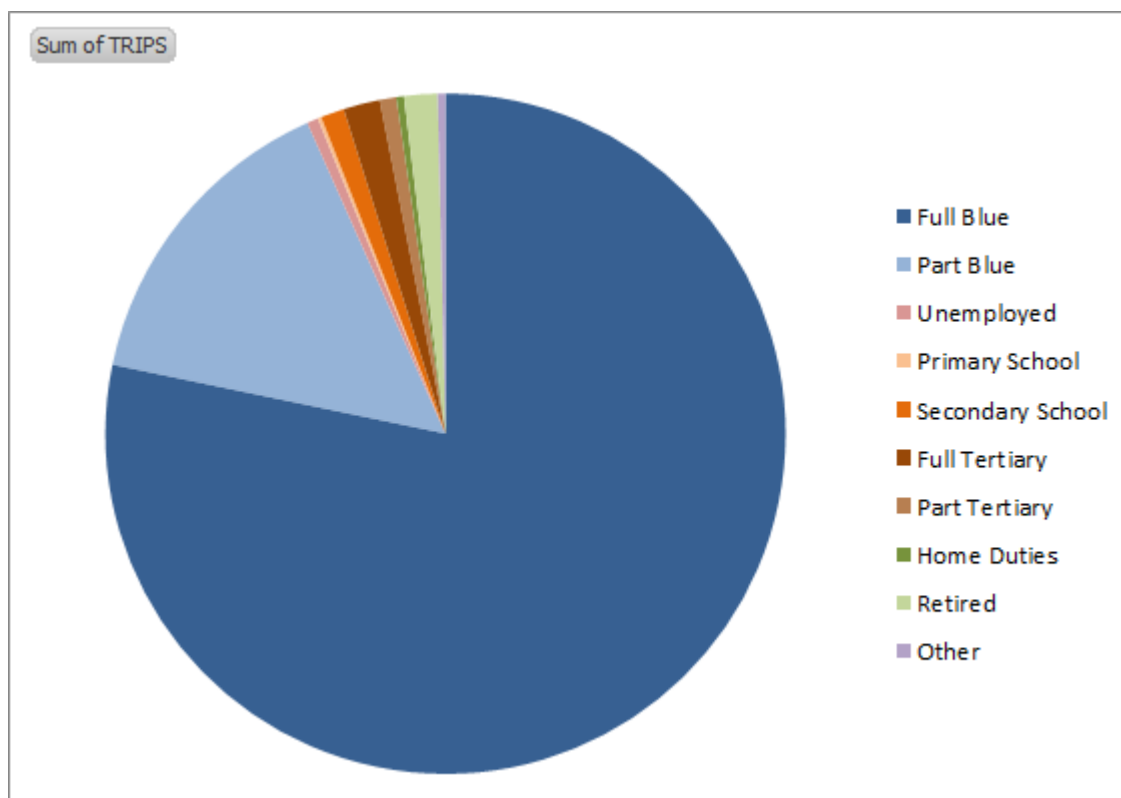
The breakdown of blue collar work trips according to the Zenith person classification is seen in Figure 9 below.

Figure 9 - The breakdown of Home Based Work - Blue Collar Trips by Zenith Variables

Unsurprisingly, over 93% of such trips are made by blue collar workers. The dependants who make blue collar work trips are students who also undertake some part time work.

A more illuminating breakdown is shown in Figure 10 below, which shows that full time blue collar workers make up 78% of trips (compared with 75% for white collar work), with part time workers accounting for 15%, and the remainder split between the various dependent categories.

Figure 10 - The Breakdown of Home Based Work - Blue Collar Trips by Main Activity

The average trip rate per person for each of the Zenith person types is shown in Figure 11 below. Blue collar workers make approximately 1.47 home based work trips per day (equivalent to 0.735 return trips). Compared with white collar workers, blue collar workers make more home based work trips (white collar workers average 1.27 trips per day).
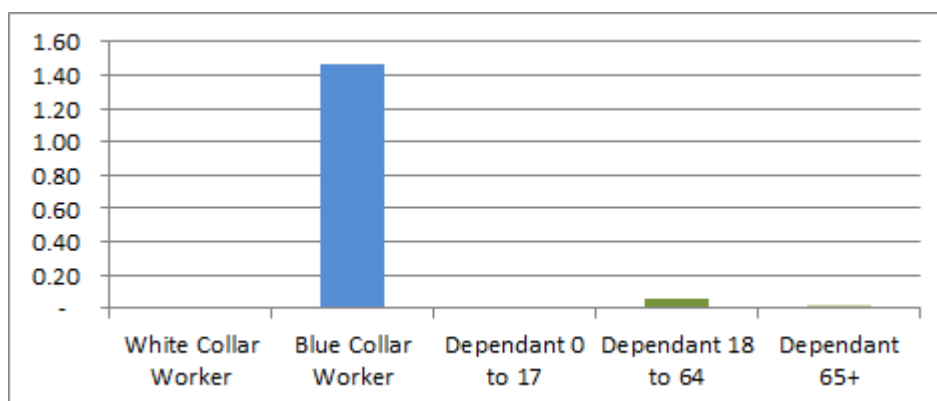
Figure 11 - Average Home Based Work – Blue Collar Trip Rate per Person by Zenith Variables

The breakdown of trip rates by main activity group is presented in Figure 12 below. As expected, part time workers have a lower observed trip rate, though they travel more frequently than their white collar equivalents (1.12 for part time blue collar, versus 0.87 for part time white collar).

This might suggest that part time blue collar workers work more regularly, but it might also suggest that part time white collar workers tend to have more added responsibilities, such as dropping the kids at school, which result in less home based work trips.
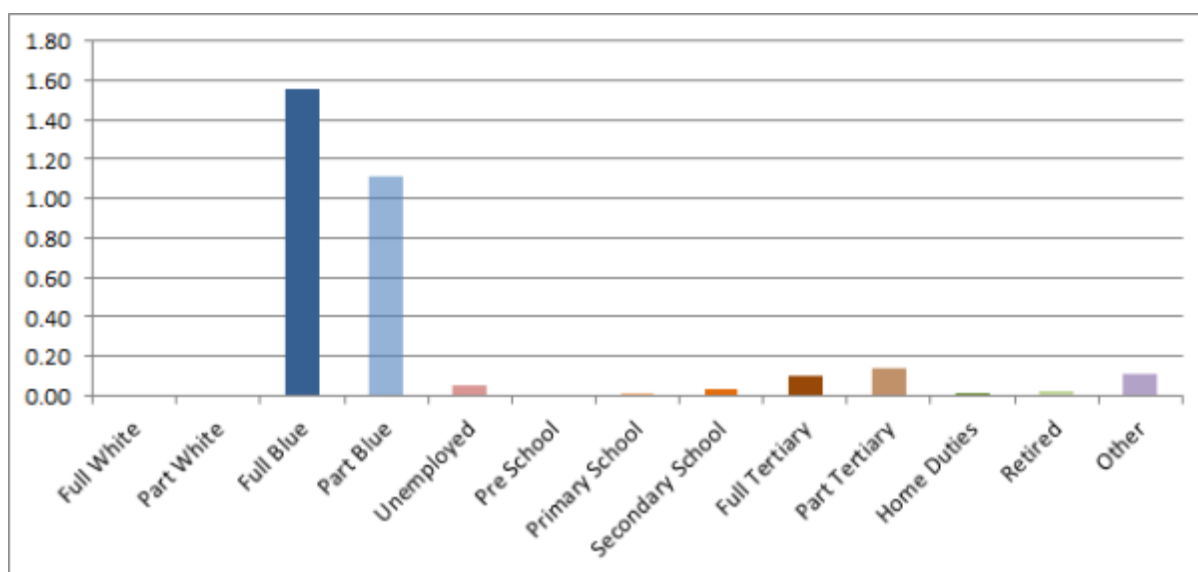
Figure 12 - Average Home Based Work - Blue Collar Trip Rate by Main Activity

5.2.2   Model Estimation

5.2.2.1   Parameter Estimates

The re-estimated model parameters for blue collar work are presented in Table 9 below.

Parameter	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE	STANDARD ERROR
BLUEWORKERS_1	1.411	58.039	0.000	0.024
BLUEWORKERS_2	2.854	52.044	0.000	0.055
BLUEWORKERS_3+	4.750	32.996	0.000	0.144
DEPS_0TO17_1+	-0.041	-1.833	0.069	0.022
DEPS_18TO64_1+	0.063	3.009	0.003	0.021
CARS_2	0.051	2.479	0.013	0.020
CARS_3+	0.125	4.057	0.000	0.031

Table 9 –Parameter Estimates and Properties for Home Based Blue Collar

The number of blue collar workers in the household has the largest impact on the number of trips, with parameters of 1.411, 2.854 and 4.75 for households with 1, 2, and 3+ blue collar workers respectively.

It is interesting to note the degree of linearity of trips in the number of blue collar workers; 2.85 is very close to double 1.41. This suggests that two households, each with 1 blue collar worker, would make a similar number of work trips to a single household with 2 blue collar workers.

As with white collar work, the presence of dependent children in a household has a negative impact on the number of blue collar work trips, with a parameter of -0.041 for any household which has 1 or more dependants aged 0-17, though the effect is much weaker (-0.40 for white collar work). This is again due to the increased likelihood of part time work among families with dependent children, and

the increased probability that another activity will be undertaken en-route to work, such as dropping the kids at school. Evidently, this burden is more likely to fall on white collar workers.

Following the pattern observed in white collar work, the presence of a dependent adult aged 18-64 has the opposite effect; a parameter of 0.063 is estimated. A dependent adult is able to take responsibility for activities such as dropping the kids at school and shopping, allowing the worker to travel directly to work.

Car ownership also has an impact on trip frequency. Relative to having no car or 1 car, the owning of 2 or 3 cars increases the average blue collar trip rate by 0.051 and 0.125 respectively.

5.2.3   Model Validation

5.2.3.1   *Demographic Validation*

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of demographic aggregation.

Referring to Table 10 below, it can be observed that:

- The blue collar work trip rate increases with household size up to a household size of four (the same pattern was observed with white collar work). The surveyed households with size six do have a higher trip rate, but that may just be due to the small sample of 103. The Zenith model's predictions generally replicate the observed patterns.
- An interesting relationship exists between income and blue collar work trips. Middle and above average income households have the highest trip rate, with the highest income households having a lower trip rate. Evidently, the highest income households are more likely to include white collar workers.
- As with white collar work, the model has a tendency to over-predict the trips of the lowest income households. The workers in these households are more likely to be part time and casual, which the model does not currently consider.
- The number of blue collar work trips increases rapidly with number of cars. This might be more usefully interpreted in an inverse manner: blue collar workers almost always own a car.
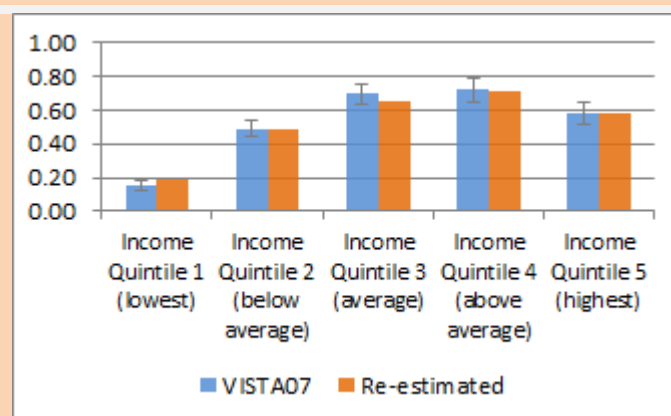
Average Household Trip Rates by Household Characteristics
## Home Based Work – Blue Collar | Re-estimated Zenith Model
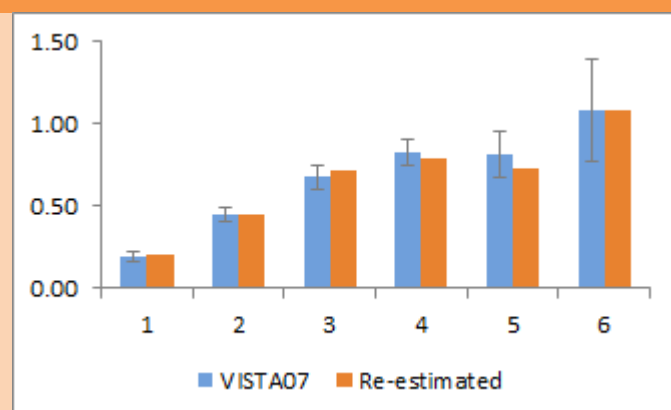
Household Size

Household Size	VISTA07	Re-estimated	Diff	95% C.I.	Sample
1	0.20	0.20	2%	± 16%	1,571
2	0.45	0.45	1%	± 9%	2,682
3	0.68	0.72	6%	± 11%	1,182
4	0.83	0.79	-5%	± 9%	1,277
5	0.81	0.73	-10%	± 17%	392
6	1.09	1.08	0%	± 28%	103

Household Income

Income Quintile	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Income Quintile 1 (lowest)	0.15	0.19	28%	± 22%	1,423
Income Quintile 2 (below average)	0.49	0.49	-1%	± 11%	1,409
Income Quintile 3 (average)	0.70	0.65	-6%	± 9%	1,467
Income Quintile 4 (above average)	0.72	0.71	-1%	± 10%	1,441
Income Quintile 5 (highest)	0.58	0.58	0%	± 11%	1,488
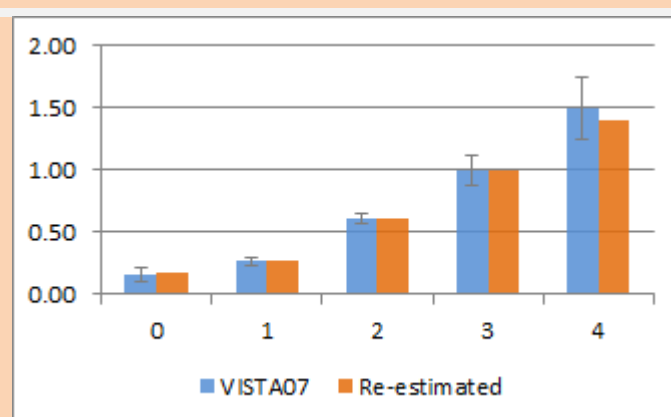
Cars Owned

Car Ownership	VISTA07	Re-estimated	Diff	95% C.I.	Sample
0	0.16	0.18	11%	± 33%	483
1	0.27	0.27	2%	± 11%	2,614
2	0.61	0.60	-1%	± 7%	3,105
3	1.00	0.99	-1%	± 11%	745
4	1.49	1.39	-7%	± 17%	225

Table 10 - Validation by Demographic Categories (Blue Collar Work)

5.2.3.2   Spatial Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of spatial aggregation.

Referring to the LGA analysis (Figure 13 and Table 11 below), it can be observed that:

- The household trip rate for blue collar work trips increases as one moves further from the Central Business District, reflecting the spatial distribution of blue collar workers in Melbourne. This pattern is opposite to that observed for white collar workers.
- There is excellent agreement between the model and the survey, with an R-Squared of 0.93 at the LGA level (compared with 0.7 for white collar work). Evidently the commuting travel of blue collar workers is more consistent and predictable. The higher proportion of full time workers in blue collar occupations, and the higher trip rate for part time workers are likely to contribute to this consistency.

There model's predictions are also in close agreement with the survey for each of the Concentric Rings (Figure 14 and Table 12).

At the SD level (Figure 15 and Table 13), Loddon (eg. Bendigo) has the highest blue collar work trip rate, at 0.6 trips per household, followed by the Central Highlands (eg. Ballarat), Barwon (eg. Geelong), and Melbourne, with an average of 0.52. The model's predicted overall trip rates for Melbourne and Geelong match the survey almost exactly, while the model is low by 10% for the Central Highlands and 8% high for Loddon. The difference may be due to sample size however, with the model's predictions falling well within 95% confidence interval bounds.

Average Household Trip Rate by LGA
Home Based Work – Blue Collar | Re-estimated Zenith Model
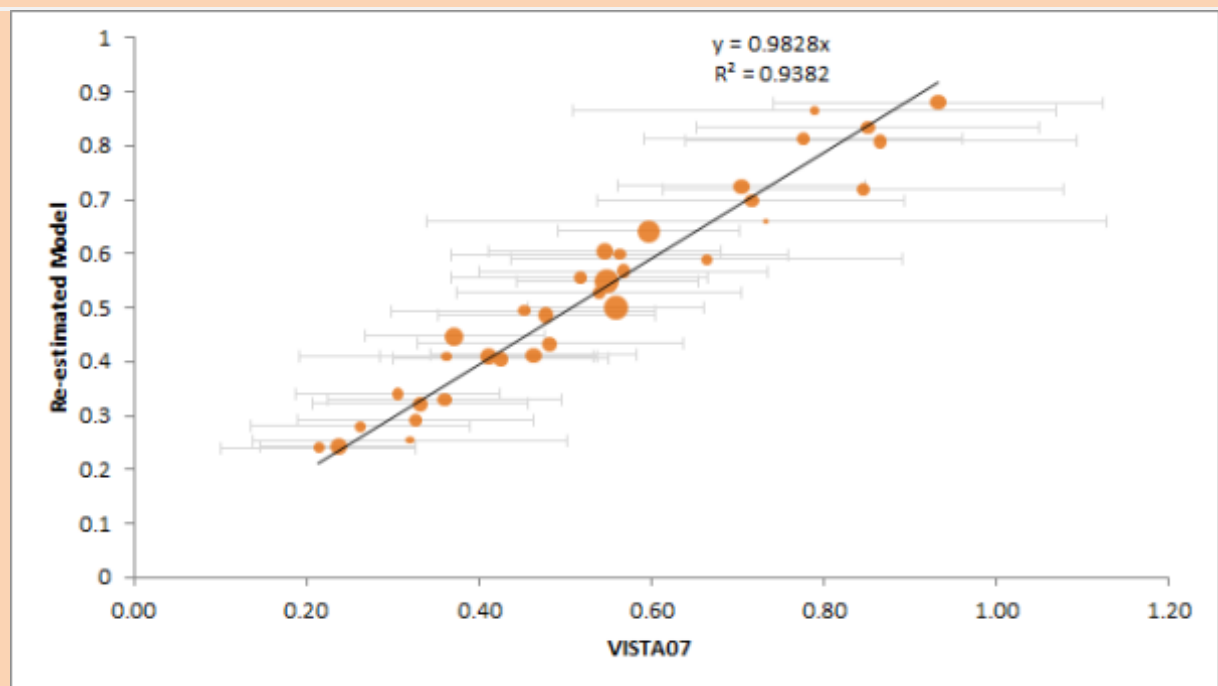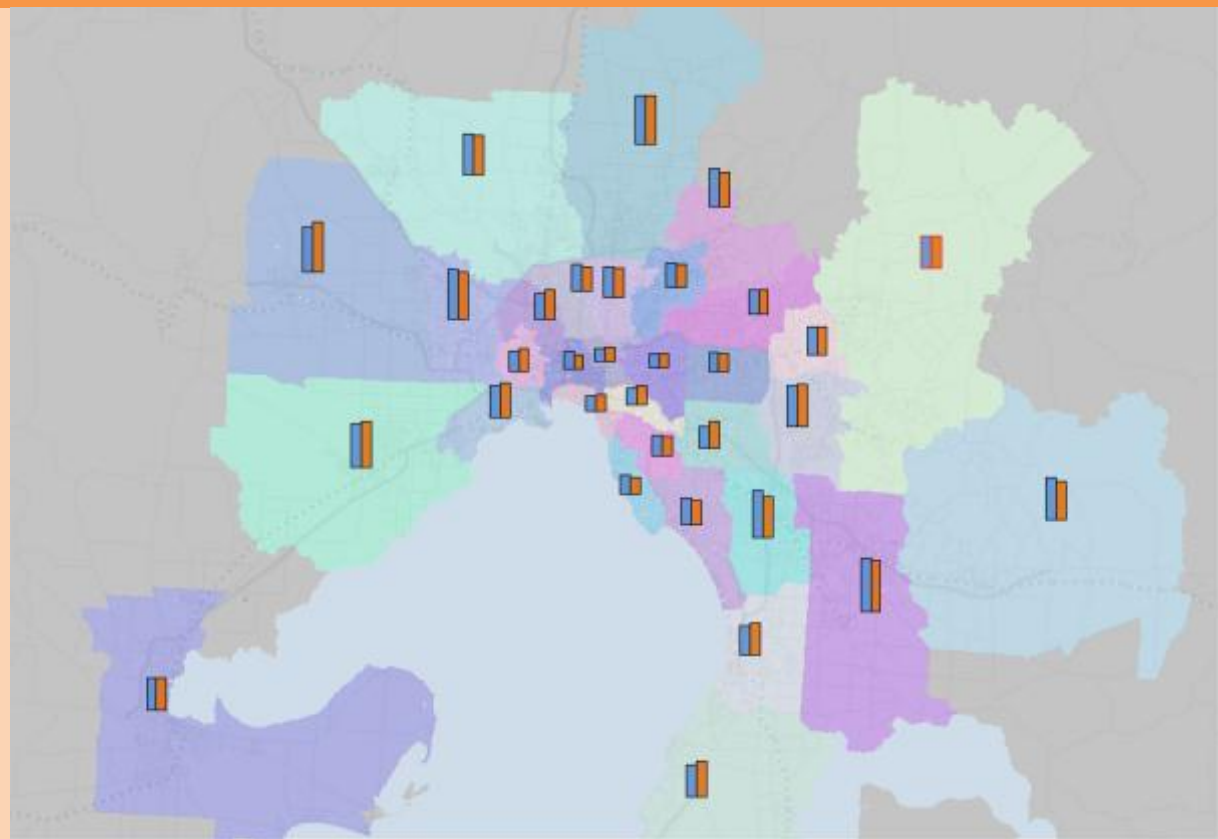
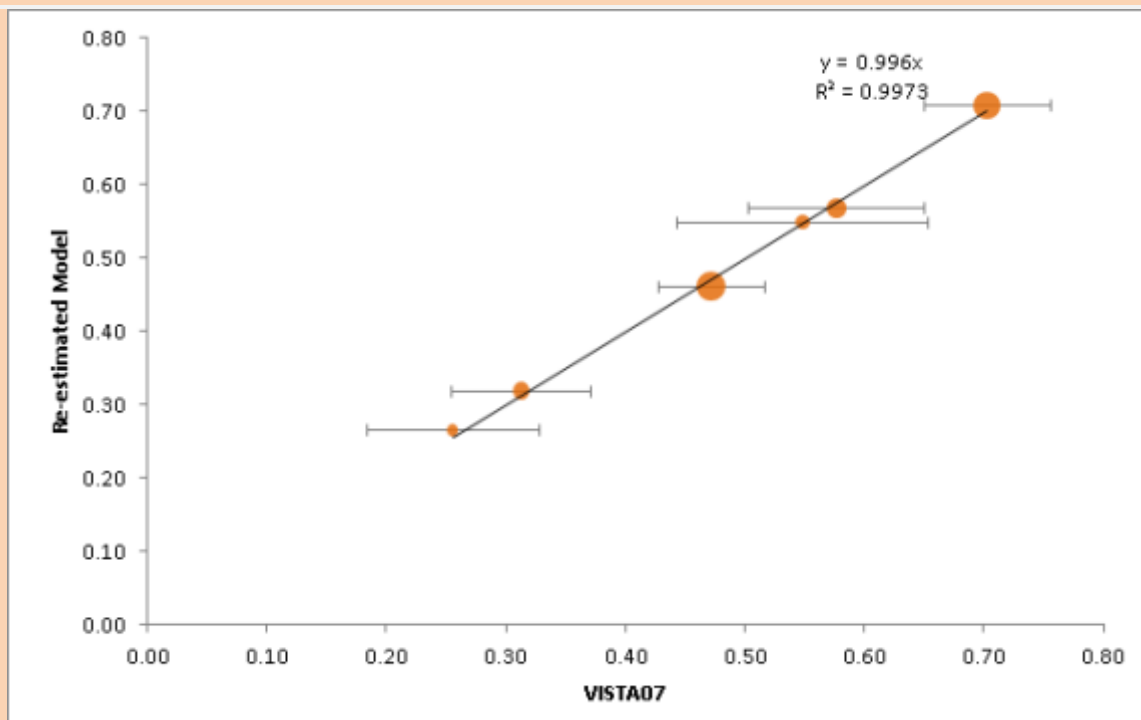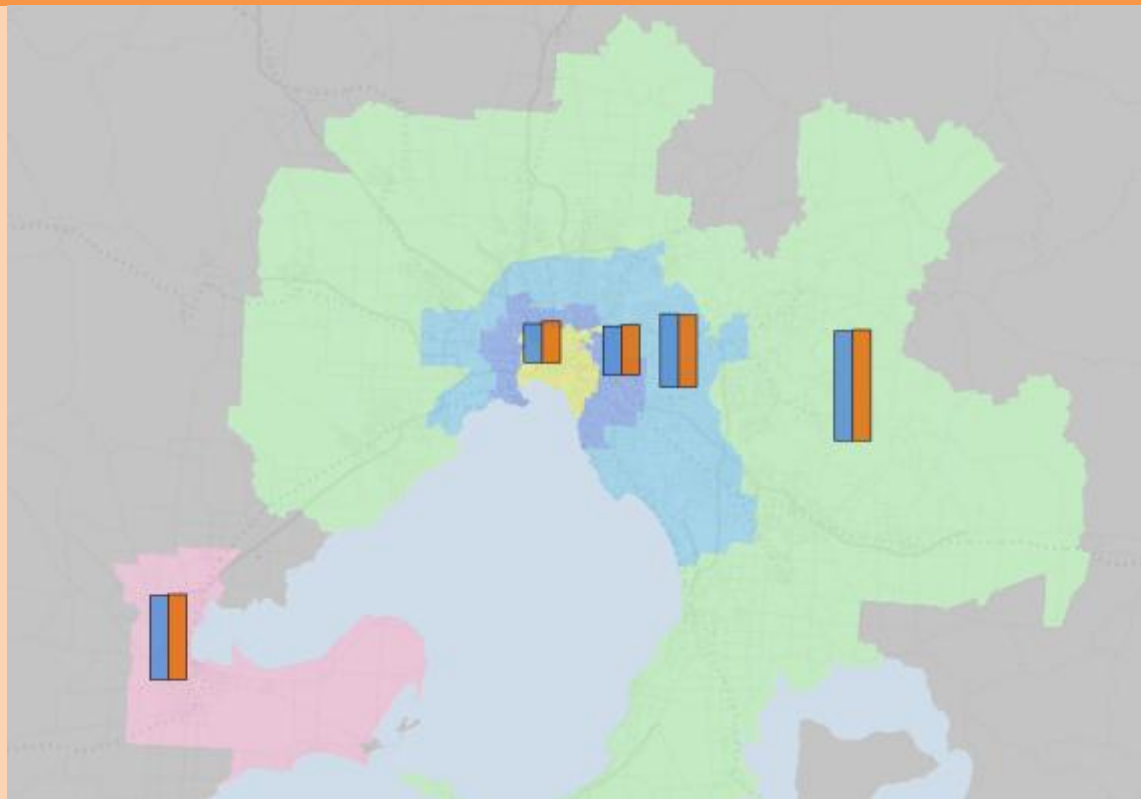*Figure 13 – Comparison of Modelled and VISTA07 Trip Rates by LGA (Blue Collar Work)*

Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Ballarat (C)	0.56	0.50	-10%	±18%	581
Banyule (C)	0.43	0.41	-5%	±29%	240
Bayside (C)	0.33	0.29	-11%	±42%	153
Boroondara (C)	0.24	0.24	3%	±38%	265
Brimbank (C)	0.87	0.81	-7%	±26%	171
Cardinia (S)	0.73	0.66	-10%	±54%	32
Casey (C)	0.93	0.88	-6%	±20%	220
Darebin (C)	0.54	0.53	-2%	±31%	194
Frankston (C)	0.52	0.56	7%	±29%	181
Glen Eira (C)	0.36	0.33	-8%	±38%	197
Greater Bendigo (C)	0.60	0.64	8%	±18%	488
Greater Dandenong (C)	0.85	0.72	-15%	±28%	167
Greater Geelong (C)	0.55	0.55	0%	±19%	572
Hobsons Bay (C)	0.56	0.60	6%	±35%	128
Hume (C)	0.72	0.70	-3%	±25%	189
Kingston (C)	0.48	0.43	-10%	±32%	225
Knox (C)	0.70	0.73	3%	±20%	223
Manningham (C)	0.41	0.41	0%	±30%	242
Maribyrnong (C)	0.36	0.41	13%	±47%	104
Maroondah (C)	0.48	0.49	2%	±26%	225
Melbourne (C)	0.32	0.25	-21%	±57%	62
Melton (S)	0.79	0.87	10%	±36%	88
Monash (C)	0.37	0.45	20%	±28%	326
Moonee Valley (C)	0.45	0.49	9%	±34%	153
Moreland (C)	0.46	0.41	-11%	±26%	239
Mornington Peninsula (S)	0.55	0.60	11%	±25%	251
Nillumbik (S)	0.66	0.59	-11%	±34%	112
Port Phillip (C)	0.26	0.28	7%	±48%	129
Stonnington (C)	0.31	0.34	12%	±39%	146
Whitehorse (C)	0.33	0.32	-3%	±38%	239
Whittlesea (C)	0.85	0.83	-2%	±23%	173
Wyndham (C)	0.78	0.81	5%	±24%	179
Yarra (C)	0.21	0.24	12%	±53%	146
Yarra Ranges (S)	0.57	0.57	0%	±29%	188

Table 11 - Comparison of Modelled and VISTA07 Trip Rates by LGA (Blue Collar Work)

Average Household Trip Rate by Region
Home Based Work – Blue Collar | Re-estimated Zenith Model

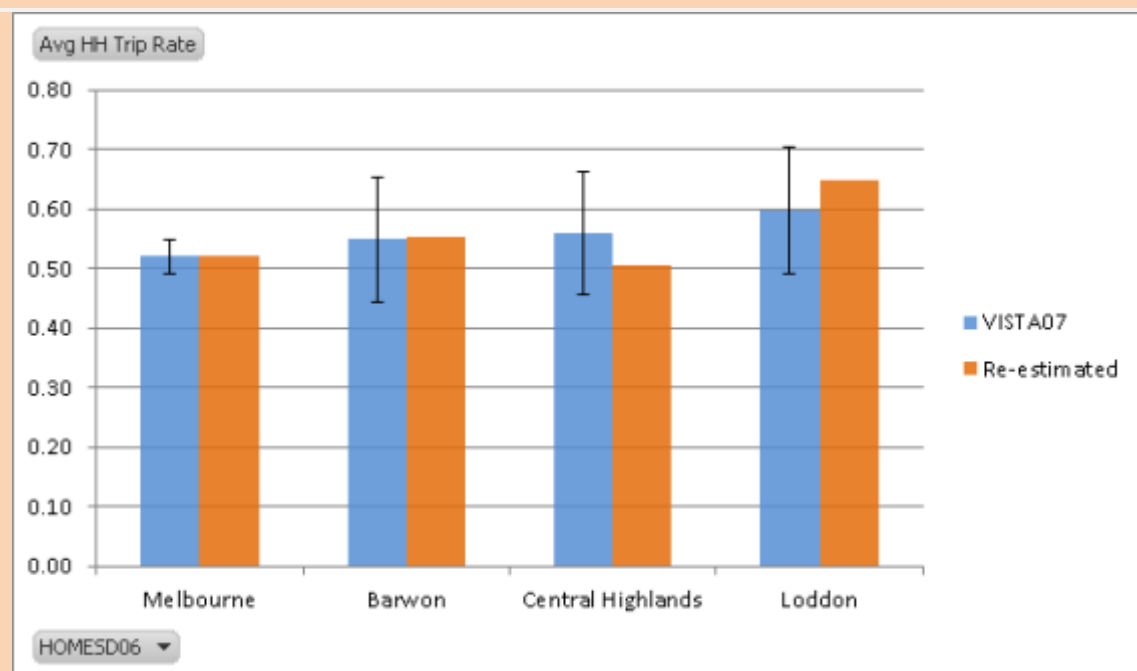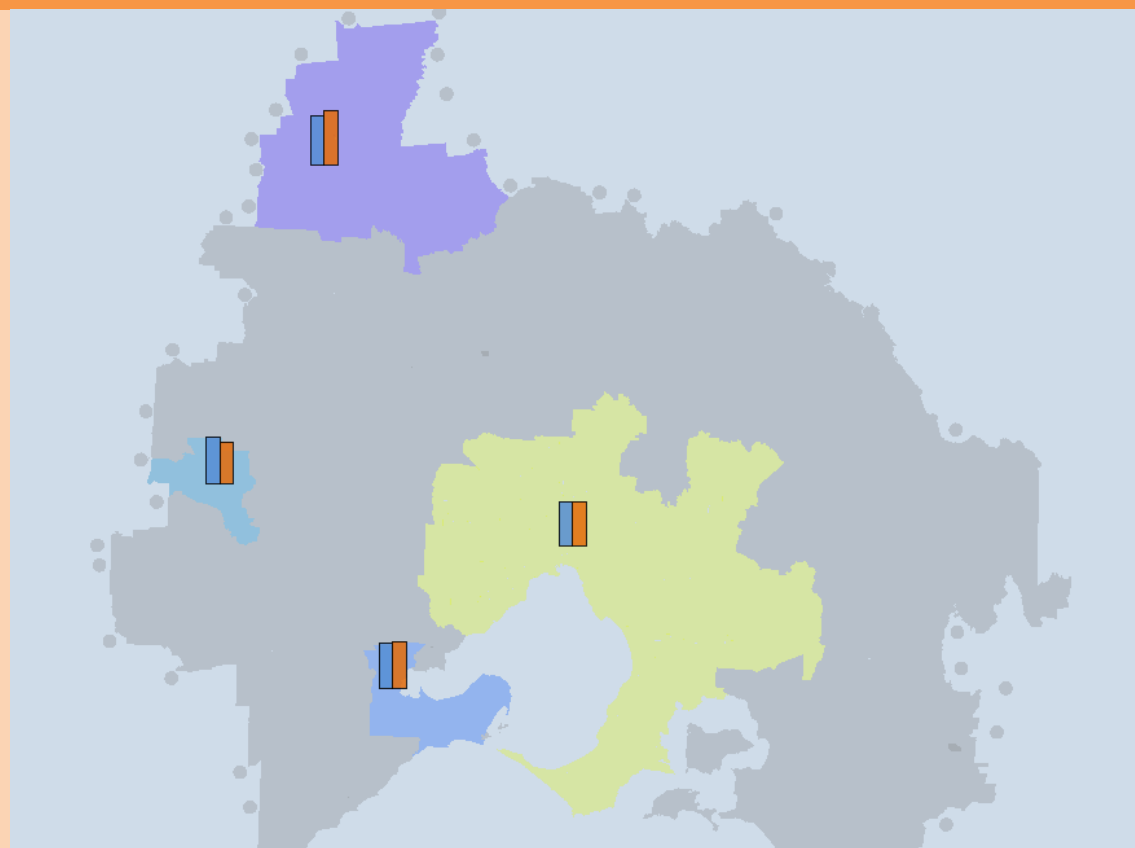*Figure 14 - Comparison of Modelled and VISTA07 Trip Rates by Region (Home Based Blue Collar)*

Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% CI	Sample
Inner City	0.26	0.26	4%	± 28%	377
Inner Suburbs	0.31	0.32	2%	± 19%	813
Middle Suburbs	0.47	0.46	-3%	± 9%	2,328
Outer Suburbs	0.70	0.71	1%	± 8%	2,069
Major Regional Centre	0.55	0.55	0%	± 19%	572
Regional	0.58	0.57	-2%	± 13%	1,069

Table 12 - Comparison of Modelled and VISTA07 Trip Rates by Region (Blue Collar Work)

Average Household Trip Rate by SD
Home Based Work – Blue Collar | Re-estimated Zenith Model

Figure 15 - Comparison of Modelled and VISTA07 Trip Rates by SD (Blue Collar Work)

Avg HH Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Melbourne	0.52	0.52	0%	± 6%	5587
Barwon	0.55	0.55	1%	± 19%	572
Central Highlands	0.56	0.51	-9%	± 18%	581
Loddon	0.60	0.65	9%	± 18%	488

Table 13 - Comparison of Modelled and VISTA07 Trip Rates by SD (Blue Collar Work)
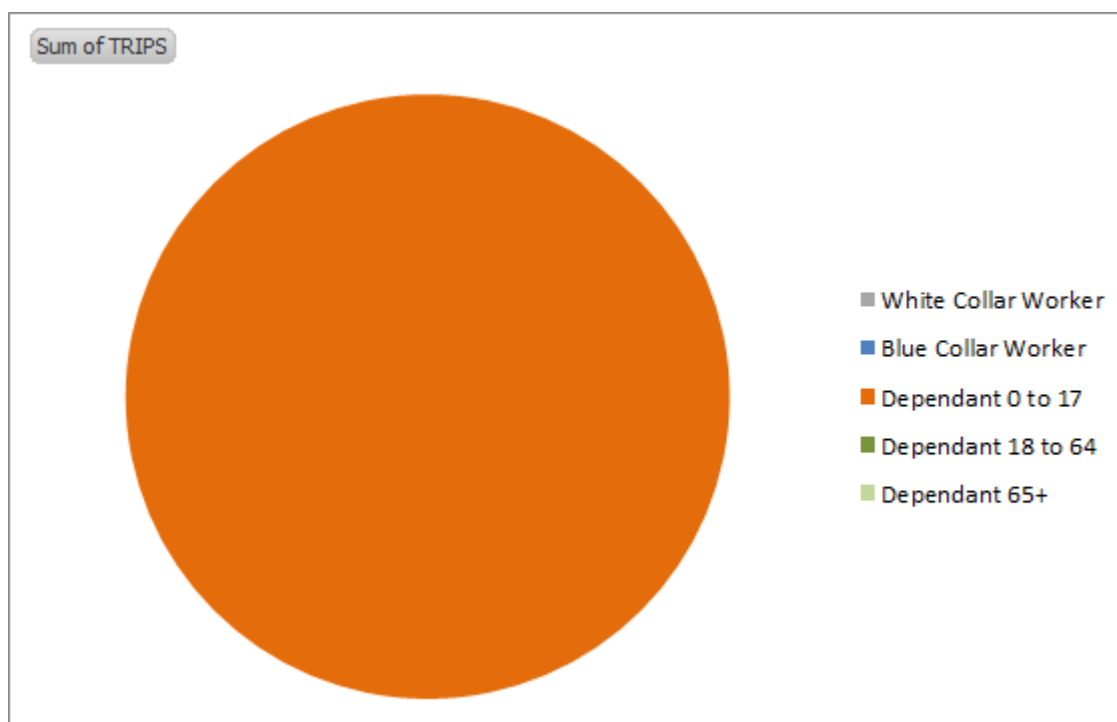
5.3 Home Based Education – Primary

5.3.1 Travel Market

This section provides a high level analysis of the market for *Home Based Education – Primary*, which we will refer to as primary school travel.
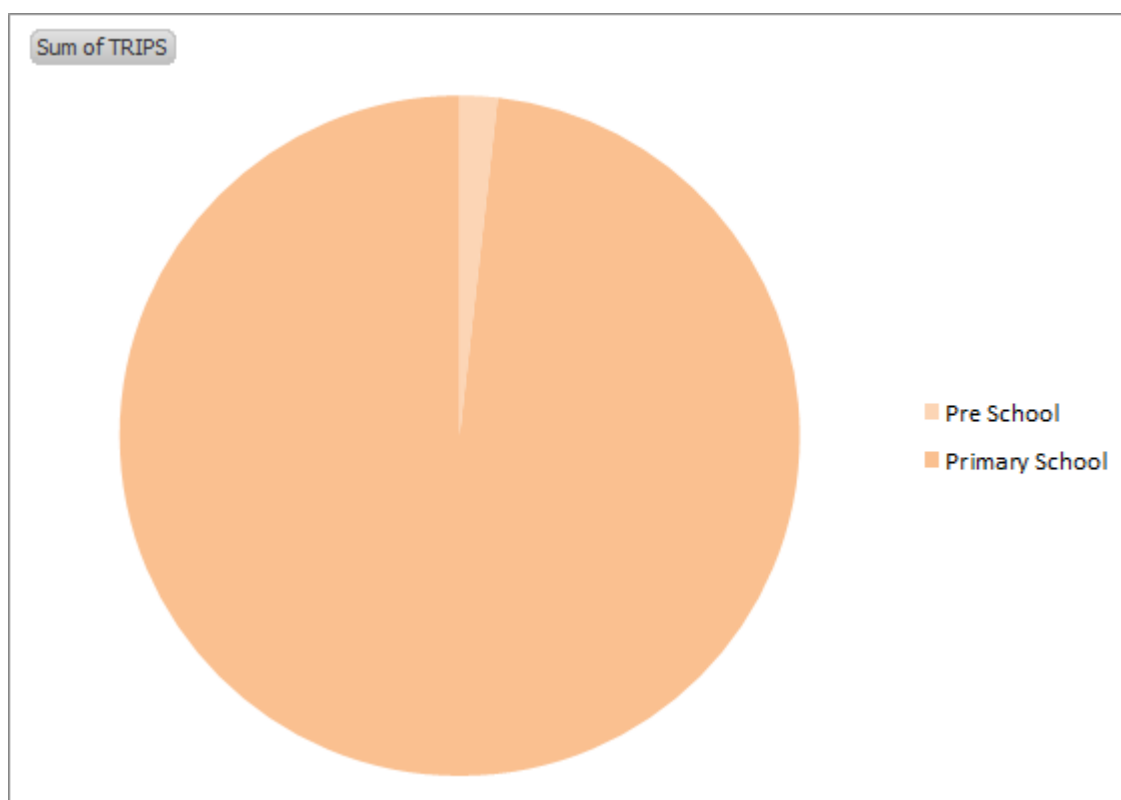
The breakdown of primary school trips according to the Zenith person classification is seen in Figure 16 below.

Figure 16 - The breakdown of Primary School Trips by Zenith Variables

Reassuringly, all of these trips are made by dependants aged 0 to 17. Note that parents dropping their kids at school are recorded as Home Based Serve Passenger / Other.

A further breakdown is shown in Figure 17 below, which shows that approximately 98% of these trips are made by children enrolled in primary school education, with the remaining 2% representing education trips made by children not yet at school (which have been coded by VLC as primary school travel).

Figure 17 - The Breakdown of Primary School Trips by Main Activity

The average trip rate per person for each of the Zenith person types is shown in Figure 18 below. On average, dependants aged 0 to 17 make 0.64 primary school trips a day.
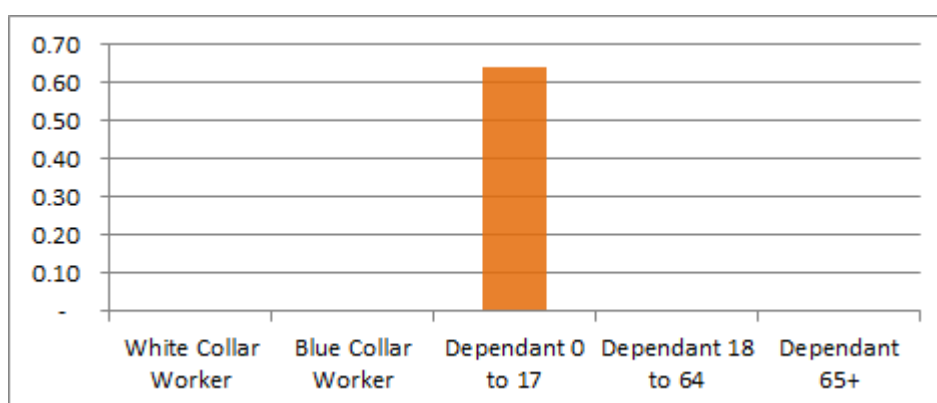
Figure 18 - Average Primary School Trip Rate per Person by Zenith Variables

A clearer analysis of trip rates is presented in Figure 19 below, which shows that primary school students make an average 1.6 primary school trips per day (equivalent to 0.8 return trips).
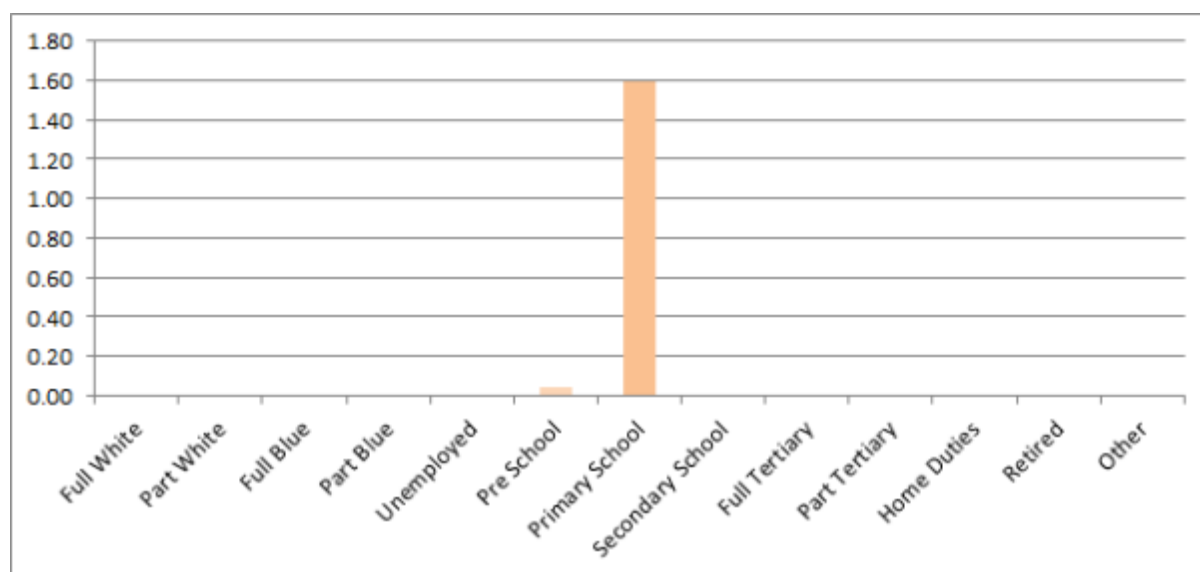
Figure 19 - Average Primary School Trip Rate by Main Activity

5.3.2   Model Estimation

5.3.2.1   Parameter Estimates

The re-estimated model parameters for primary school travel are presented in Table 14 below.

Parameter	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE	STANDARD ERROR
DEPS_0TO17_1	0.382	10.938	0.000	0.035
DEPS_0TO17_2	1.410	42.543	0.000	0.033
DEPS_0TO17_3+	2.556	48.948	0.000	0.052
DEPS_18TO64_1	-0.036	-1.402	0.161	0.026

Table 14 –Parameter Estimates and Properties for Primary School Travel

The number of primary school trips is closely related to the number of dependants aged 0-17. Households with 1, 2 and 3+ such dependants will average 0.382, 1.41 and 2.556 trips per day, with a deduction of 0.036 for households that have exactly 1 dependant aged 18 to 64.

The relationship between the number of dependants aged 0 to 17 and the number of trips is far from linear (1.41 is nearly 3.7 times 0.382). Two households, each having 1 dependant aged 0 to 17 will make less trips (on average) than one household having 2 such dependants (2 x 0.382 is much less than 1.41). This suggests that only children are less likely to be in primary school, all other things being equal. One might hypothesise that many of them are not yet at school, and that their parents may have additional children at a later date. A simple analysis of the Census could confirm this.

Interestingly, the presence of an adult dependant (aged 18-64) slightly reduces the trip rate of primary school travel by 0.036 trips per day. A likely explanation is that the dependant adult picks the child up from school, and makes a stop on the way home (eg. at the shops), replacing the home based primary school trip with a shopping based other trip, and a home based shopping trip. Interestingly,

this effect is not observable for households with 2 or more adult dependants (potentially due to a lack of sample size).

The number of white or blue collar workers, or dependants aged 65+ has not been found to have a significant impact on the frequency of primary school travel; nor has the level of household car ownership.

5.3.3   Model Validation

5.3.3.1   Demographic Validation

The re-estimated Zenith model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of demographic aggregation.

Referring to Table 15 below, it can be observed that:

- Households with 1 or 2 people make virtually no primary school trips (such households are unlikely to have any primary school children)
- As the household size increases from 3 to 5, the primary school trip rate increases dramatically. The model's predictions also reflect this trend.
- The primary school trip rate increases generally with income, but appears to decrease slightly for the highest income households. Interestingly, the model tends to under-predict the primary school trips made by low income households, and conversely over-predict the trip making of high income households. A likely explanation is that households with dependants aged 0 to 17 increase their income levels as their children grow older and reach high school age (eg. mothers re-entering the workforce, or as parents progress in their profession). As such, lower incomes would be correlated with having primary school age children, and higher incomes with secondary school children. As the model makes no distinction between primary or secondary school age children, this would cause the model to under-predict primary school, and over-predict secondary school trip rates for low income households, and vice versa for high income households. This explanation is backed by the later analysis of secondary school travel.
- Households with 2 cars make significantly more primary school trips than other households. This is likely to be a feature of households with primary school age children; they tend to have 2 cars.
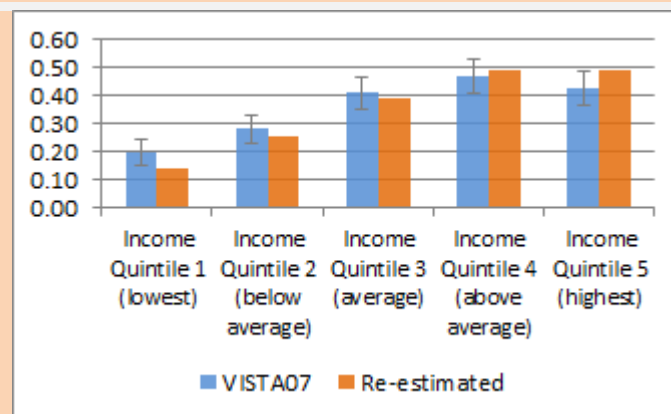
Average Household Trip Rates by Household Characteristics
### Home Based Education – Primary | Re-estimated Zenith Model
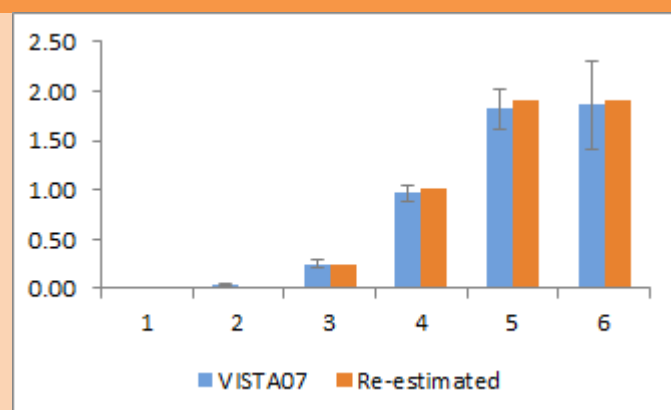
Household Size

Household Size	VISTA07	Re-estimated	Diff	95% C.I.	Sample
1	0.00	-0.01	NA	± 0%	1,571
2	0.03	0.01	-76%	± 30%	2,682
3	0.25	0.24	-2%	± 19%	1,182
4	0.97	1.01	4%	± 9%	1,277
5	1.82	1.92	5%	± 11%	392
6	1.87	1.90	2%	± 24%	103

Household Income

Income Quintile	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Income Quintile 1 (lowest)	0.20	0.14	-28%	± 23%	1,423
Income Quintile 2 (below average)	0.28	0.26	-8%	± 18%	1,409
Income Quintile 3 (average)	0.41	0.39	-4%	± 14%	1,467
Income Quintile 4 (above average)	0.47	0.49	5%	± 13%	1,441
Income Quintile 5 (highest)	0.43	0.49	14%	± 14%	1,488
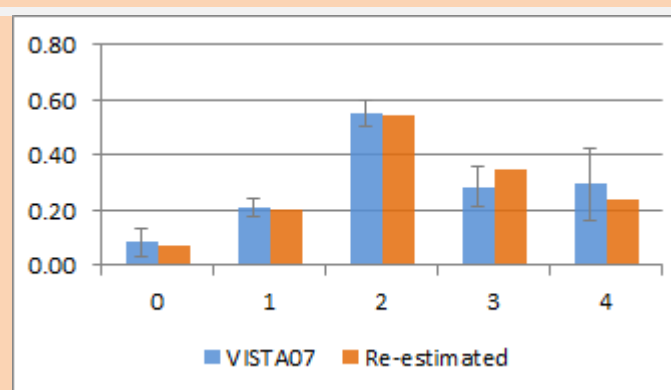
Cars Owned

Car Ownership	VISTA07	Re-estimated	Diff	95% C.I.	Sample
0	0.08	0.07	-11%	± 57%	483
1	0.21	0.20	-3%	± 14%	2,614
2	0.55	0.54	-2%	± 8%	3,105
3	0.29	0.35	21%	± 25%	745
4	0.29	0.24	-19%	± 45%	225

Table 15 - Validation by Demographic Categories (Primary School Trips)

5.3.3.2 Spatial Validation

The re-estimated Zenith model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of spatial aggregation.

Referring to the LGA analysis (Figure 20 and Table 16 below), it can be observed that:

- Primary school trip rates tend to increase as one moves from the inner to outer suburbs of Melbourne,
- The Zenith model's predicted trip rates for each LGA correlate fairly well with the trip rates from the survey sample. While the R-Squared of 0.57 is not overly high, there is considerable uncertainty in the survey estimates (due to sample size), with 31 of the 34 modelled predictions lying within a 95% confidence interval of the surveyed result.

A more interesting pattern emerges by examining the Concentric Ring analysis (Figure 21 and Table 17 below). The model tends to slightly over-predict trip rates for the inner and middle suburbs by about 5%, and under-predict trip rates for the outer suburbs by about 10%. Most likely this is due to the proportion of 0-17 year olds who are primary school children being above average in the outer suburbs, and below average in the inner and middle suburbs.

A model which explicitly included primary school age children would account for this, and may be worth exploring at a later date.

At the SD level (Figure 22 and Table 18), the most noteworthy pattern is the low trip rate in Geelong, which the model does not fully replicate (the model over-predicts primary school trips for Geelong). It seems that Geelong (at least the surveyed sample) has a lower proportion of primary school age children.

Average Household Trip Rate by LGA
Home Based Education – Primary | Re-estimated Zenith Model
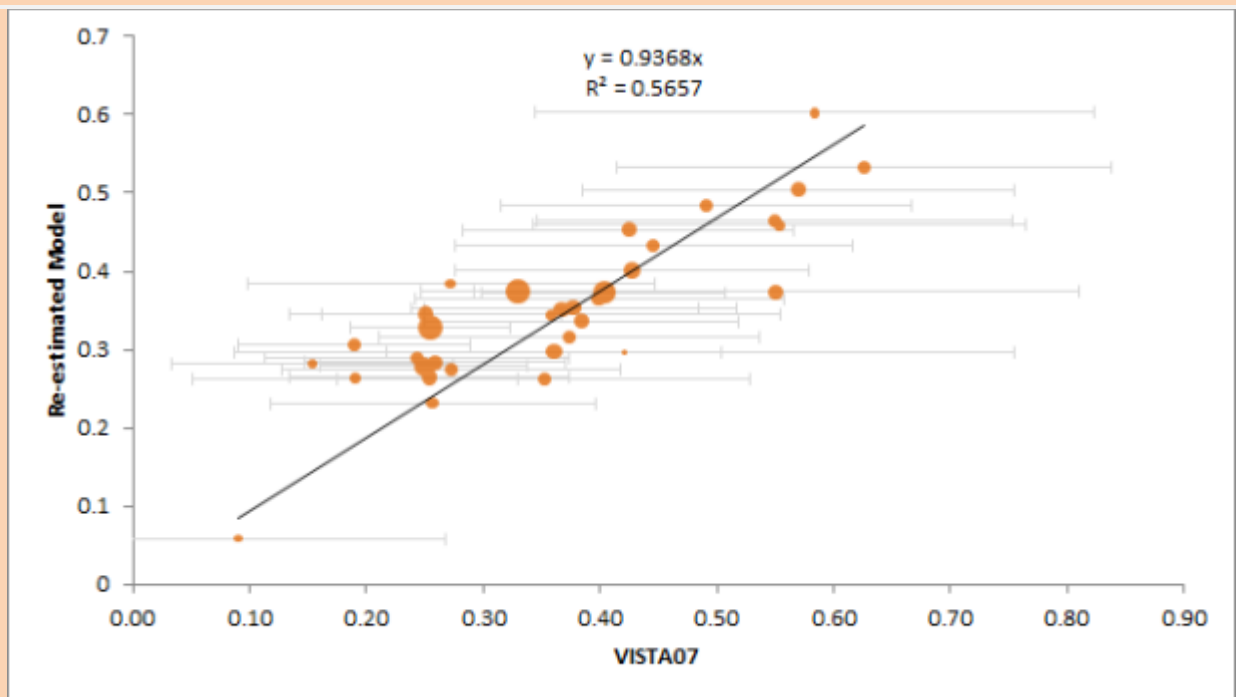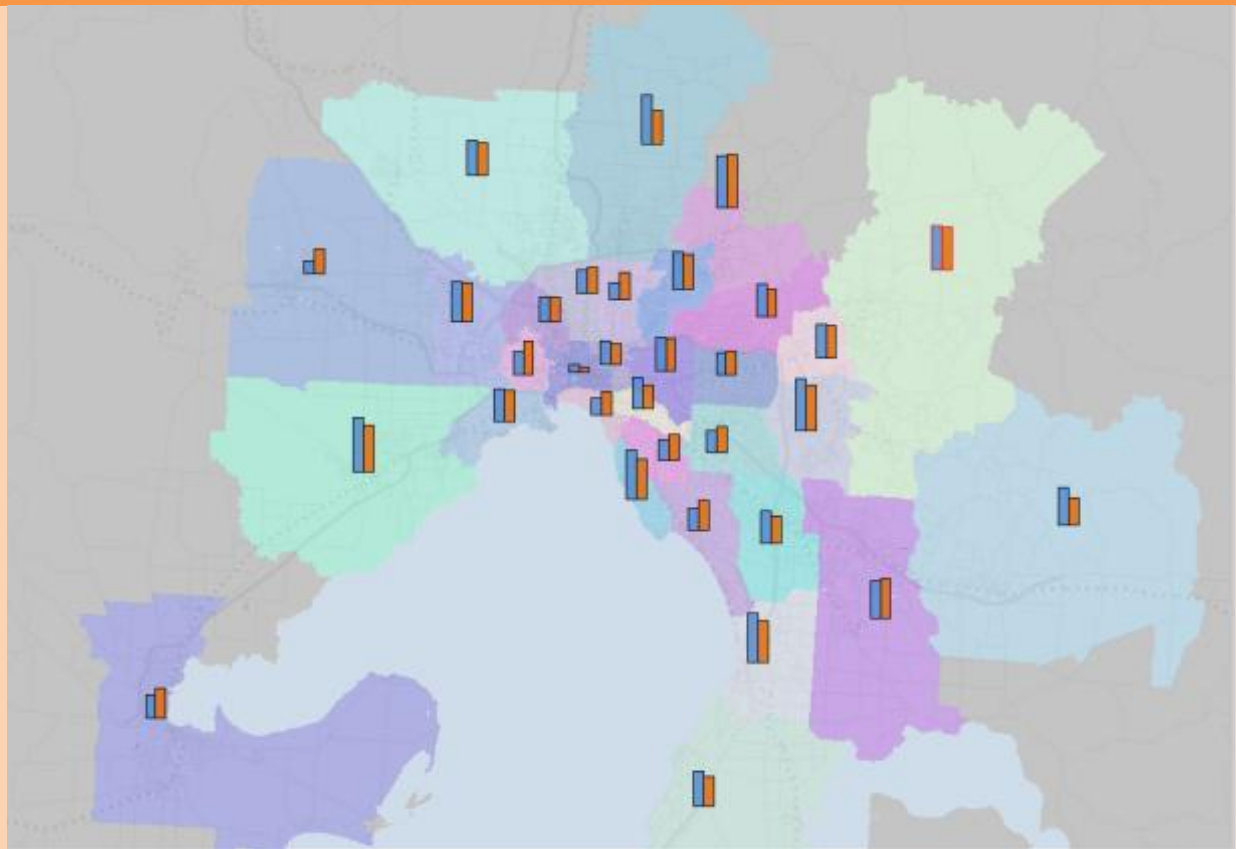
Figure 20 – Comparison of Modelled and VISTA07 Trip Rates by LGA (Primary School Trips)

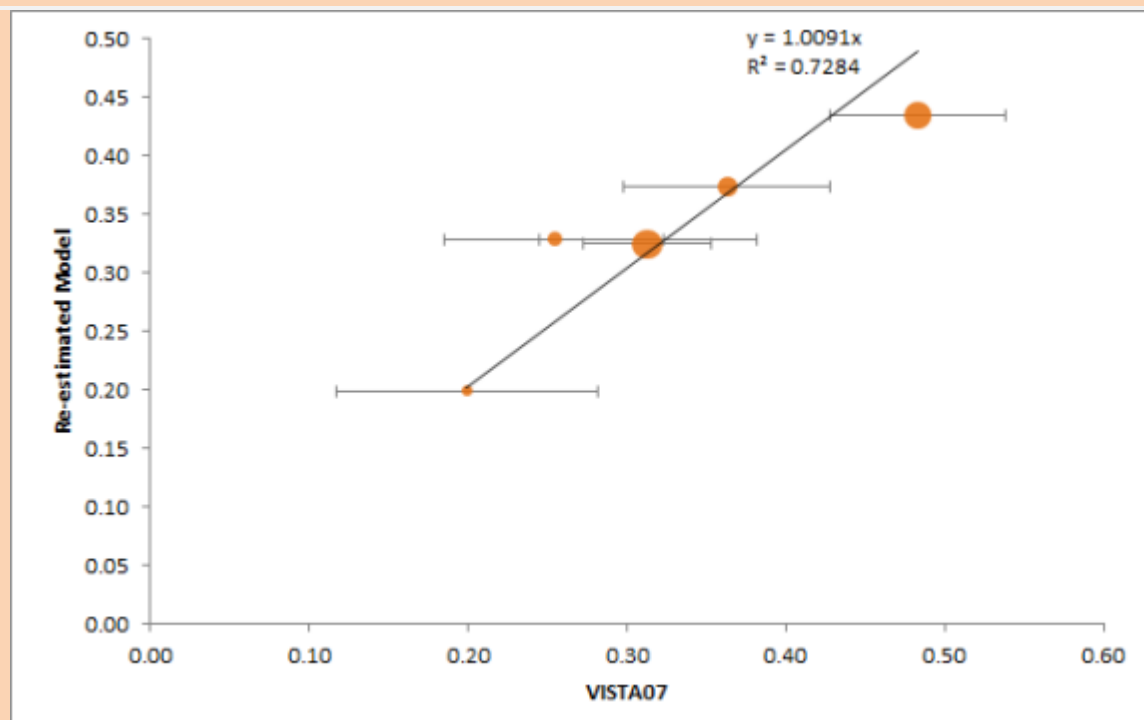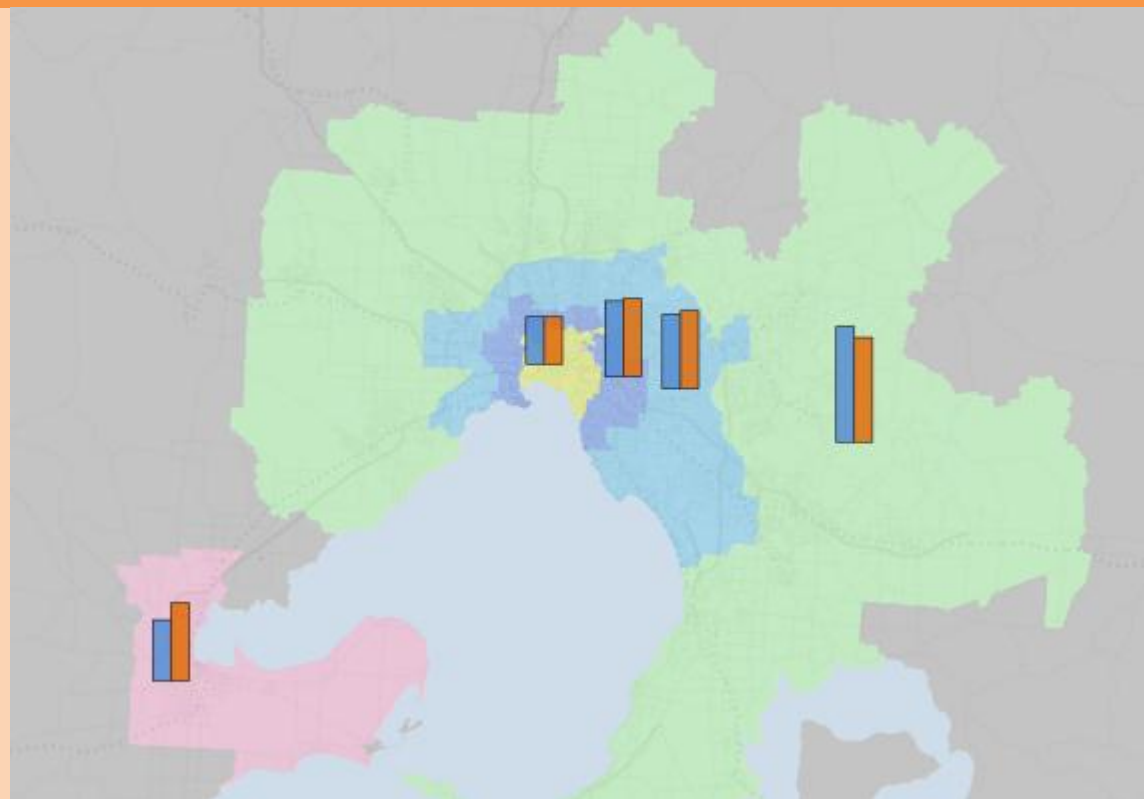| Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Ballarat (C)	0.33	0.37	14%	±25%	581
Banyule (C)	0.43	0.40	-6%	±35%	240
Bayside (C)	0.55	0.46	-17%	±38%	153
Boroondara (C)	0.37	0.35	-4%	±32%	265
Brimbank (C)	0.45	0.43	-3%	±38%	171
Cardinia (S)	0.42	0.30	-29%	±79%	32
Casey (C)	0.42	0.45	7%	±33%	220
Darebin (C)	0.19	0.31	62%	±53%	194
Frankston (C)	0.55	0.46	-15%	±37%	181
Glen Eira (C)	0.24	0.29	19%	±53%	197
Greater Bendigo (C)	0.40	0.37	-8%	±26%	488
Greater Dandenong (C)	0.37	0.32	-16%	±43%	167
Greater Geelong (C)	0.25	0.33	29%	±27%	572
Hobsons Bay (C)	0.36	0.34	-4%	±55%	128
Hume (C)	0.40	0.37	-9%	±40%	189
Kingston (C)	0.25	0.35	38%	±47%	225
Knox (C)	0.57	0.50	-11%	±33%	223
Manningham (C)	0.36	0.30	-17%	±40%	242
Maribyrnong (C)	0.27	0.38	41%	±64%	104
Maroondah (C)	0.38	0.35	-6%	±37%	225
Melbourne (C)	0.09	0.06	-35%	±196%	62
Melton (S)	0.15	0.28	83%	±78%	88
Monash (C)	0.25	0.28	12%	±36%	326
Moonee Valley (C)	0.27	0.27	1%	±53%	153
Moreland (C)	0.26	0.28	10%	±43%	239
Mornington Peninsula (S)	0.38	0.34	-12%	±35%	251
Nillumbik (S)	0.58	0.60	3%	±41%	112
Port Phillip (C)	0.19	0.26	38%	±73%	129
Stonnington (C)	0.35	0.26	-25%	±50%	146
Whitehorse (C)	0.25	0.27	4%	±47%	239
Whittlesea (C)	0.55	0.37	-32%	±47%	173
Wyndham (C)	0.63	0.53	-15%	±34%	179
Yarra (C)	0.26	0.23	-10%	±54%	146
Yarra Ranges (S)	0.49	0.48	-2%	±36%	188

Table 16 - Comparison of Modelled AND VISTA07 Trip Rates by LGA (Primary School Trips)

Average Household Trip Rate by Region
Home Based Education – Primary| Re-estimated Zenith Model

Figure 21 - Comparison of Modelled and VISTA07 Trip Rates by Region (Primary School Trips)

Avg Household Trip Rate	VISTA07	Re-estimated	Diff	95% CI	Sample
Inner City	0.20	0.20	0%	± 41%	377
Inner Suburbs	0.31	0.33	5%	± 22%	813
Middle Suburbs	0.31	0.32	4%	± 13%	2,328
Outer Suburbs	0.48	0.43	-10%	± 11%	2,069
Major Regional Centre	0.25	0.33	29%	± 27%	572
Regional	0.36	0.37	3%	± 18%	1,069

Table 17 - Comparison of Modelled and VISTA07 Trip Rates by Region (Primary School Trips)

Average Household Trip Rate by SD
Home Based Education – Primary | Re-estimated Zenith Model

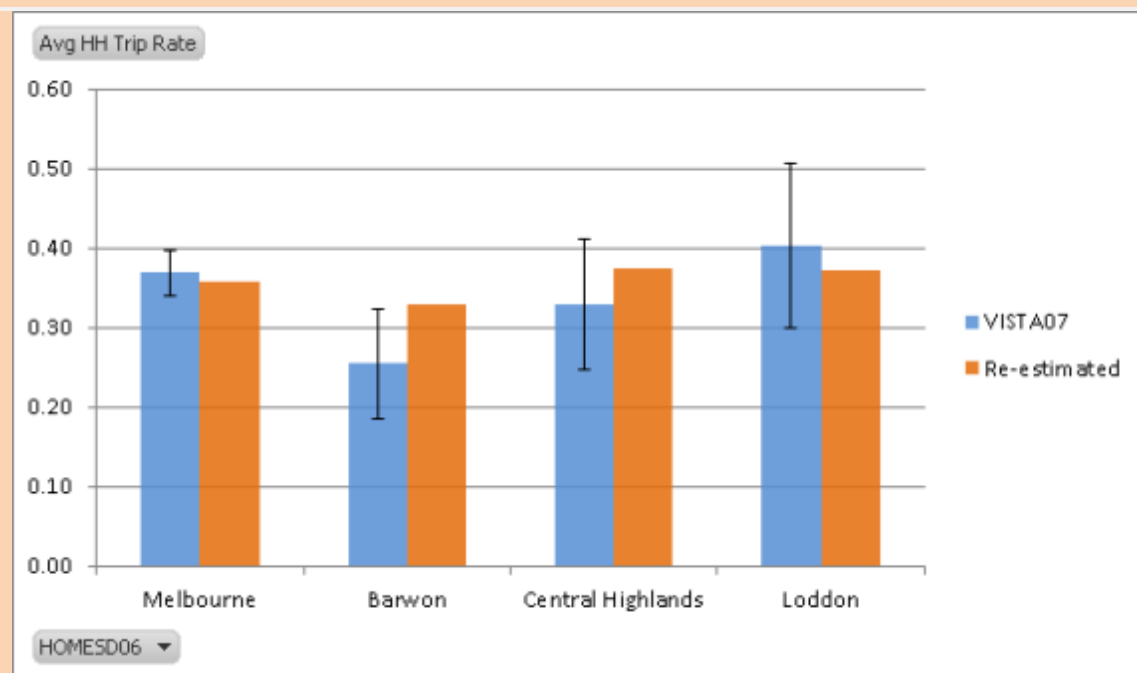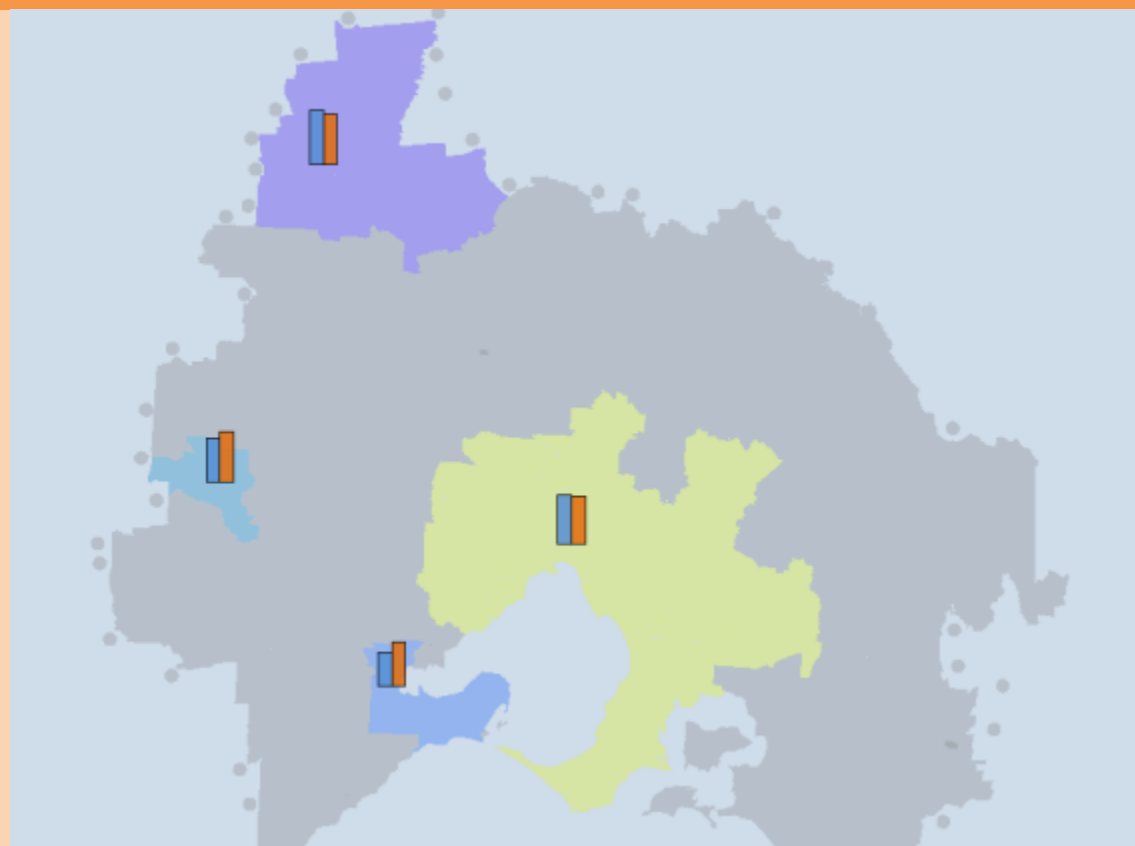*Figure 22 - Comparison of Modelled and VISTA07 Trip Rates by SD (Primary School Trips)*

Avg HH Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Melbourne	0.37	0.36	-3%	± 8%	5587
Barwon	0.25	0.33	29%	± 27%	572
Central Highlands	0.33	0.38	14%	± 25%	581
Loddon	0.40	0.37	-8%	± 26%	488

Table 18 - Comparison of Modelled and VISTA07 Trip Rates by SD (Primary School Trips)
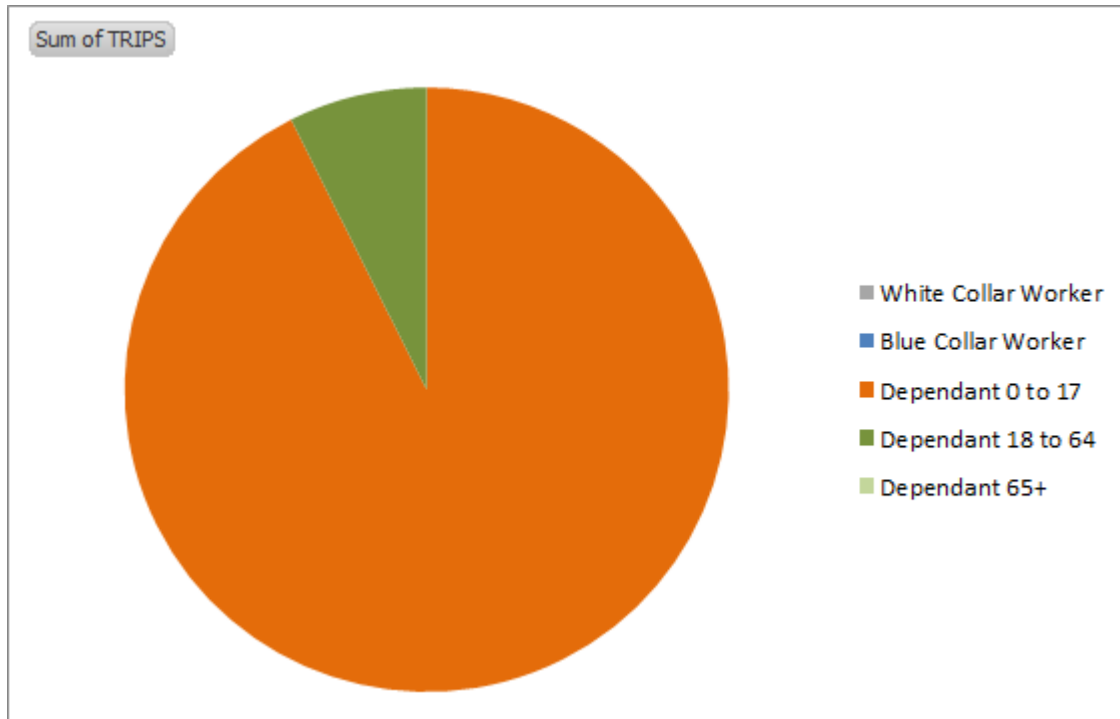
5.4   Home Based Education – Secondary

5.4.1   Travel Market

This section provides a high level analysis of the market for *Home Based Education – Secondary,* which we will refer to as secondary school travel.
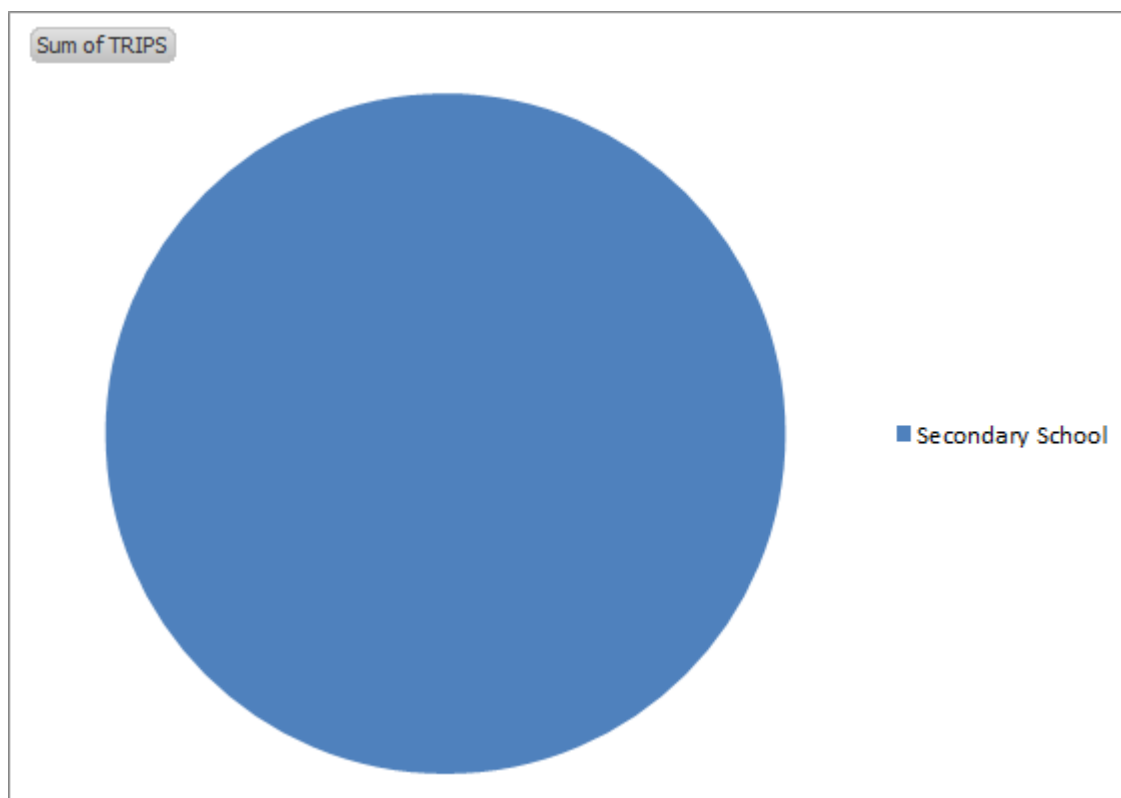
The breakdown of secondary school trips according to this classification is seen in Figure 23 below.

Figure 23 - The breakdown of Secondary School Trips by Zenith Variables

Approximately 93% of these trips are made by dependants aged 0 to 17, the remainder are dependants 18 to 64; presumably 18 year olds who are in their final year of secondary school. Final year secondary students typically turn 18 during their final year. As such, it may make sense to modify the dependant age category to 0 to 18 in the future, or explicitly model secondary students as a separate category of person.

This is supported Figure 24 below, which shows that all secondary school trips are made by secondary school students; trips made by parents dropping / picking up their kids from school are recorded as Home Based Serve Passenger / Other trips.

Figure 24 - The Breakdown of Secondary School Trips by Main Activity

The average trip rate per person for each of the Zenith person types is shown in Figure 25 below. On average, dependants aged 0 to 17 make 0.5 secondary school trips a day, while dependants aged 18 to 64 contribute another 0.06 per day.
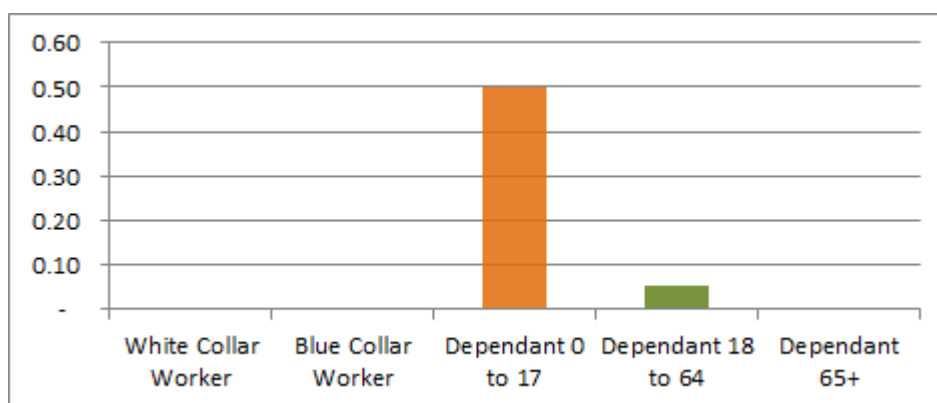
Figure 25 - Average Secondary School Trip Rate per Person by Zenith Variables

Both of these categories are coarse proxies for secondary school students; if one confines the analysis to secondary school students, the average daily trip rate is 1.66 (as seen in Figure 26 below). Clearly, a model which separated secondary school students would be better able to predict secondary school travel. This may be worth exploring at a later date.
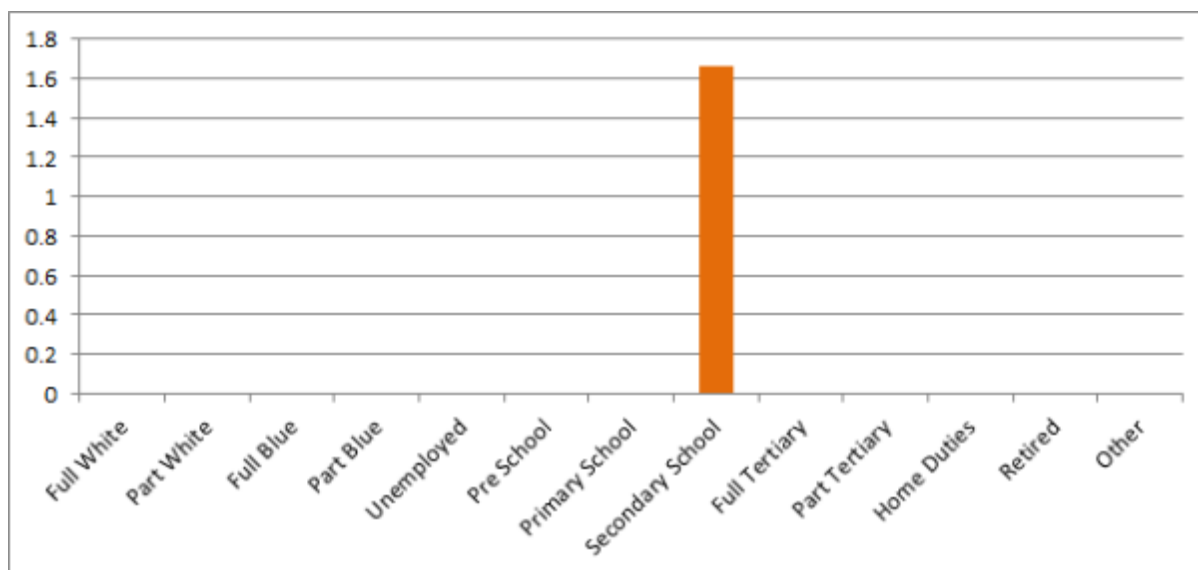
Figure 26 - Average Secondary School Trip Rate by Main Activity

5.4.2 Model Estimation

5.4.2.1 Parameter Estimates

The re-estimated model parameters for secondary school travel are presented in Table 19 below.

Parameter	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE	STANDARD ERROR
DEPS_0TO17_1	0.671	18.298	0.000	0.037
DEPS_0TO17_2	0.980	28.383	0.000	0.035
DEPS_0TO17_3+	1.422	26.166	0.000	0.054
DEPS_18TO64_1	-0.057	-2.124	0.035	0.027
DEPS_18TO64_2	0.243	4.571	0.000	0.053
DEPS_18TO64_3+	0.496	4.007	0.000	0.124

Table 19 –Parameter Estimates and Properties for Secondary School Travel

As expected, the number of dependants aged 0-17 in the household has the largest impact on the number of trips, with parameters of 0.671, 0.98, and 1.422 for households with 1, 2, and 3+ dependants aged 0-17 respectively. The presence of a single adult dependant (aged 18 to 64) slightly reduces the trip rate of secondary school travel, with a parameter of –0.046. As with primary school travel, the likely explanation is that this adult dependant might drop off / pick up the child up from school, and make a stop on the way, such as shopping.

It is also interesting to note the large parameters on households with 2 or 3+ adult dependants. This indicates that if a household has more than one adult dependant, there is a good chance that at least one of them is an 18 year old school student.

This explanation is in no way elegant, and reflects the fact that 0-17 does not cover the full range of secondary school students. A much more elegant and predictive model would include secondary school students explicitly (or at the very least adjust the age group to be 0-18).

5.4.3   Model Validation

5.4.3.1   Demographic Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of demographic aggregation.

Referring to Table 20 below, it can be observed that:

- As with primary school travel, very few secondary school trips are made by households with 1 or 2 people. The secondary school trip rate rises sharply as household size increases from three to six. In the main, the model replicates the pattern observed in the survey, but with a slight tendency to over-predict the trip rate for 3 person households, and under-predict for 6 person households.
- The model tends to under-estimate secondary school trips for high income households, and vice versa for low income households. The opposite effect was found with primary school. Taken together, the evidence suggests that households with secondary school children will have (on average) a higher income than households with primary school children. This is a correlational, rather than causal effect linking income with the rate of primary and secondary school trip making. Being a correlational effect, including income in the model is not the ideal solution; rather, it suggests we should separate primary and secondary school children.
- The model tends to under-estimate the secondary school trips of households which own 3 or more cars.
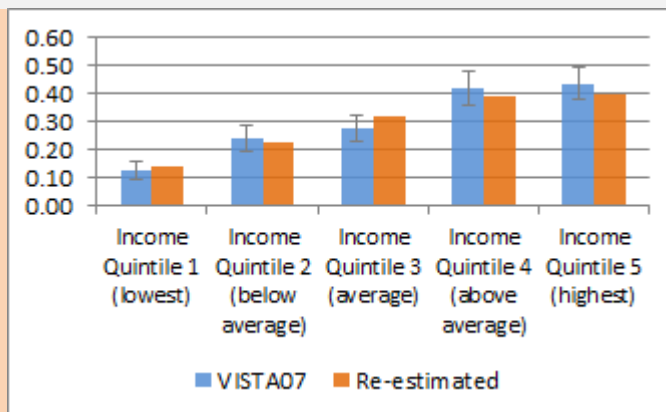
Average Household Trip Rates by Household Characteristics
### Home Based Education – Secondary | Re-estimated Zenith Model
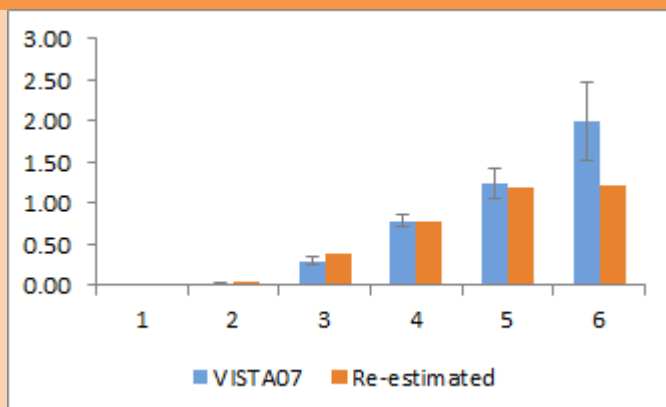
Household Size

Household Size	VISTA07	Re-estimated	Diff	95% C.I.	Sample
1	0.00	-0.01	NA	± 0%	1,571
2	0.03	0.04	7%	± 31%	2,682
3	0.30	0.38	27%	± 16%	1,182
4	0.79	0.77	-3%	± 10%	1,277
5	1.24	1.19	-4%	± 14%	392
6	1.99	1.21	-39%	± 24%	103

Household Income

Income Quintile	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Income Quintile 1 (lowest)	0.12	0.14	14%	± 26%	1,423
Income Quintile 2 (below average)	0.24	0.23	-7%	± 19%	1,409
Income Quintile 3 (average)	0.28	0.32	16%	± 16%	1,467
Income Quintile 4 (above average)	0.42	0.39	-7%	± 15%	1,441
Income Quintile 5 (highest)	0.44	0.40	-9%	± 14%	1,488
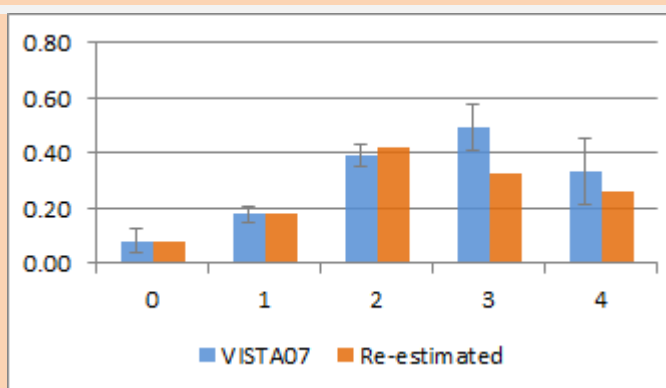
Cars Owned

Car Ownership	VISTA07	Re-estimated	Diff	95% C.I.	Sample
0	0.08	0.08	2%	± 55%	483
1	0.18	0.18	2%	± 17%	2,614
2	0.39	0.42	8%	± 10%	3,105
3	0.49	0.33	-34%	± 17%	745
4	0.34	0.26	-23%	± 35%	225

Table 20 - Validation by Demographic Categories (Secondary School Trips)

5.4.3.2 Spatial Validation

The re-estimated Zenith model has been applied to the responding households in VISTA07, with predicted and actual trip rates compared at various levels of spatial aggregation.

Referring to the LGA analysis (Figure 27 and Table 21), it can be observed that:

- The surveyed secondary school trip rate in Inner Melbourne is very low; most families with secondary school children live in the suburbs.
- There is a great deal of variation in trip rate between LGAs. For the most part, we don't think this variation reflects real differences between LGAs (as indicated by the wide error bars), but instead reflects randomness in the sample for each LGA (exacerbated by the low average trip rate for secondary school travel).
- The model does a fairly poor job of predicting the trip rate for individual LGAs. Rather than interpreting this spatially, however, we believe that this is reflective of the model's inability to accurately predict the secondary school trips for small groups of households (each LGA has an average sample of 213 households). This is due to the coarse nature of the 0-17 age group as a predictor of secondary school travel.

The secondary school model is more able to predict differences for larger groups of households, where the proportion of under 17s who are of secondary school age approaches the mean.

This is illustrated in the analysis at the Concentric Ring level (Figure 28 and Table 22), where the model successfully predicts the higher trip rate of the outer suburbs, and the lower trip rate of the inner city (though the model does over-predict the inner city somewhat).

At the SD level (Figure 29 and Table 23), there is a great deal of uniformity of secondary school trip rates, both in the survey and in the model. Trip rates vary between 0.29 and 0.31.

Average Household Trip Rate by LGA
Home Based Education – Secondary | Re-estimated Zenith Model
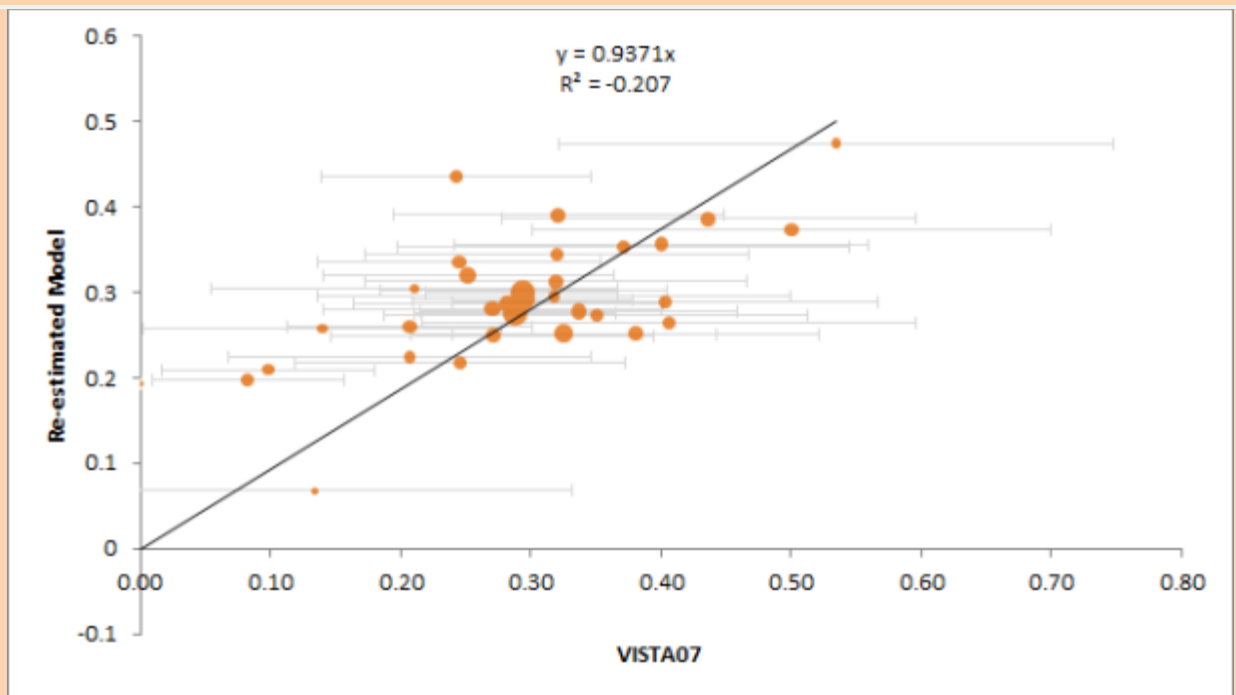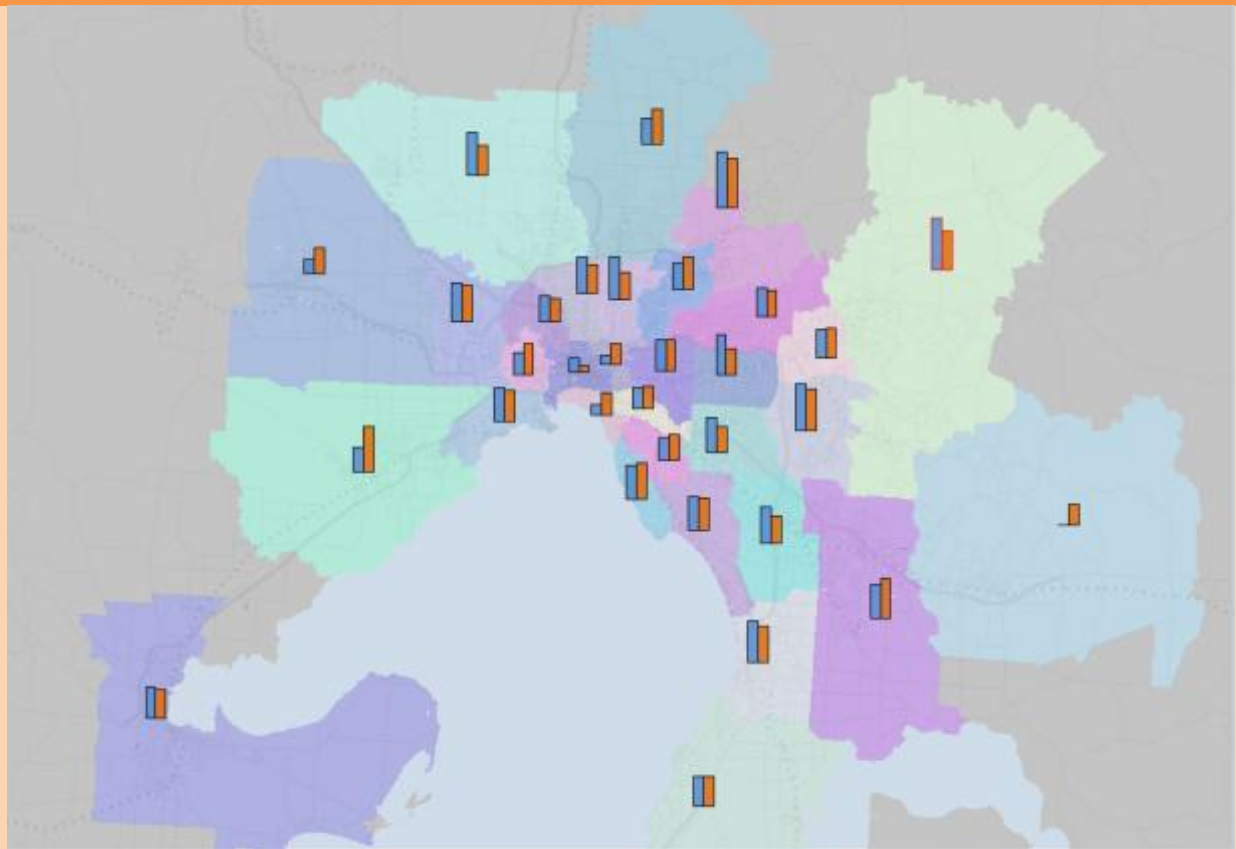
Figure 27 – Comparison of Modelled and VISTA07 Trip Rates by LGA (Secondary School Trips)

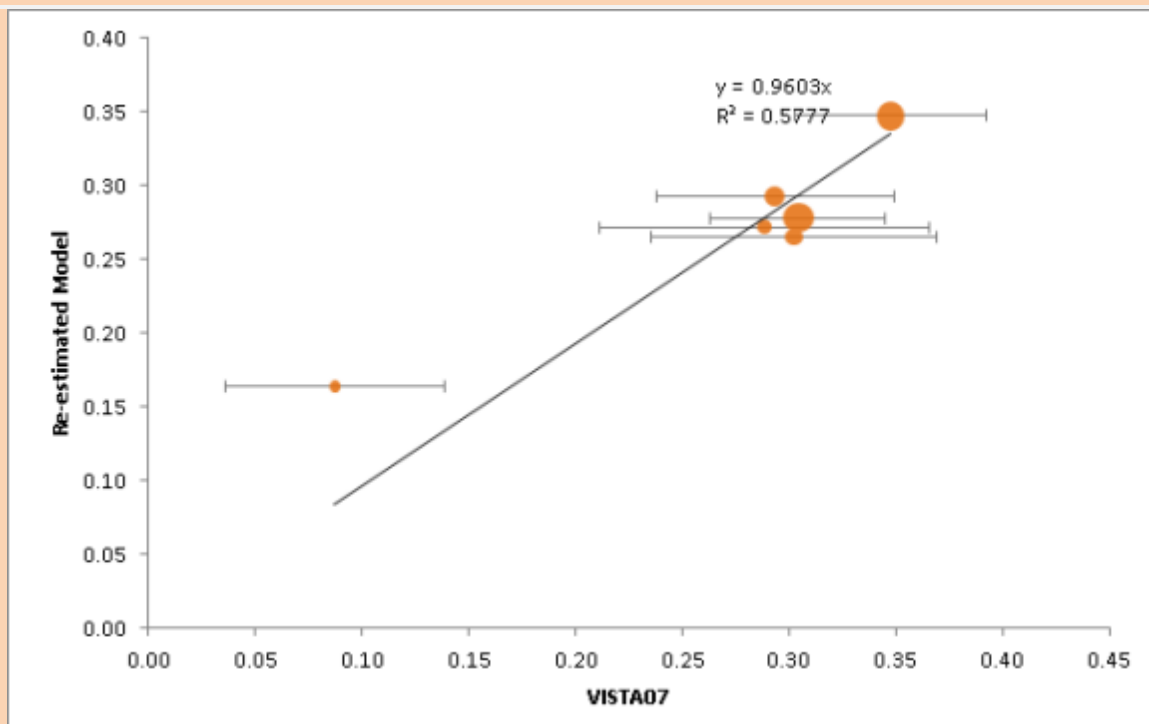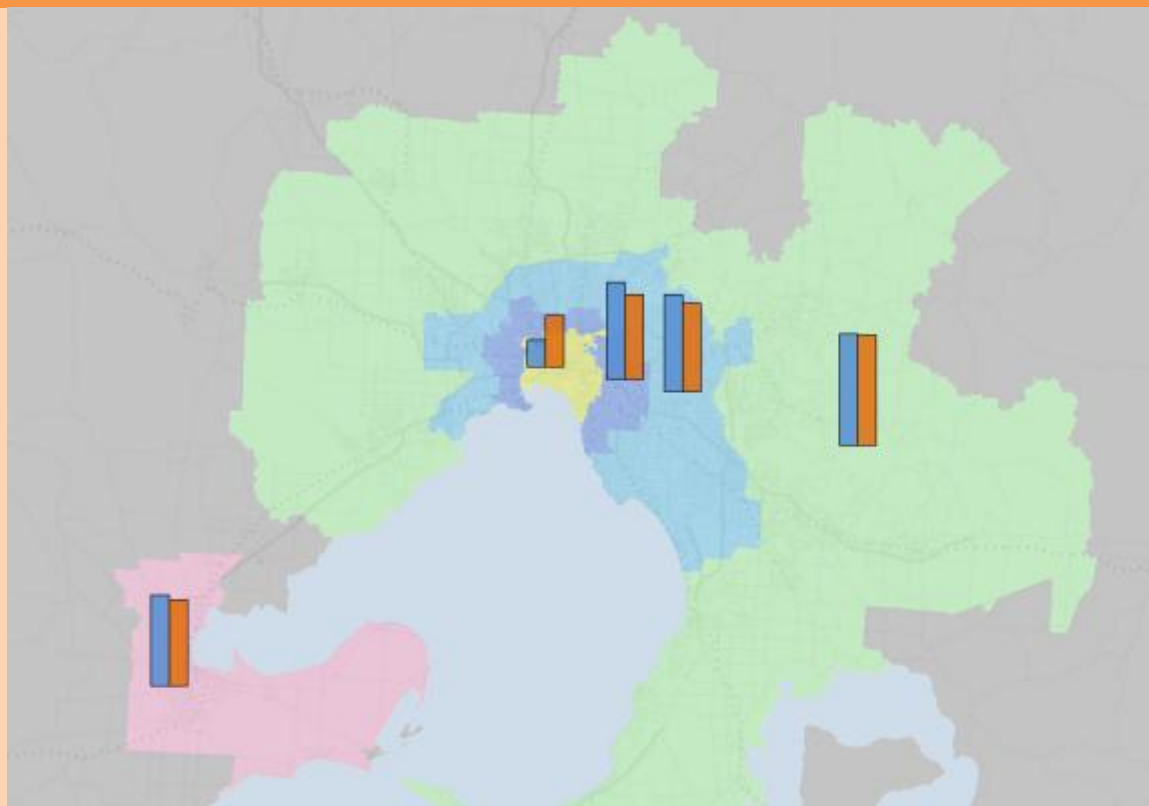| Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Ballarat (C)	0.29	0.30	2%	±25%	581
Banyule (C)	0.25	0.32	27%	±44%	240
Bayside (C)	0.32	0.34	8%	±46%	153
Boroondara (C)	0.29	0.30	3%	±37%	265
Brimbank (C)	0.37	0.35	-5%	±47%	171
Cardinia (S)	0.00	0.19	NA	NA	32
Casey (C)	0.32	0.39	22%	±40%	220
Darebin (C)	0.41	0.26	-35%	±47%	194
Frankston (C)	0.40	0.36	-11%	±40%	181
Glen Eira (C)	0.21	0.26	26%	±45%	197
Greater Bendigo (C)	0.29	0.29	-1%	±29%	488
Greater Dandenong (C)	0.35	0.27	-22%	±47%	167
Greater Geelong (C)	0.29	0.28	-4%	±27%	572
Hobsons Bay (C)	0.32	0.30	-7%	±57%	128
Hume (C)	0.40	0.29	-28%	±41%	189
Kingston (C)	0.32	0.31	-2%	±46%	225
Knox (C)	0.44	0.39	-11%	±36%	223
Manningham (C)	0.27	0.25	-8%	±46%	242
Maribyrnong (C)	0.21	0.30	44%	±74%	104
Maroondah (C)	0.27	0.28	4%	±48%	225
Melbourne (C)	0.13	0.07	-49%	±147%	62
Melton (S)	0.14	0.26	84%	±99%	88
Monash (C)	0.33	0.25	-22%	±36%	326
Moonee Valley (C)	0.25	0.22	-11%	±52%	153
Moreland (C)	0.34	0.28	-17%	±36%	239
Mornington Peninsula (S)	0.28	0.29	1%	±42%	251
Nillumbik (S)	0.53	0.47	-11%	±40%	112
Port Phillip (C)	0.10	0.21	114%	±84%	129
Stonnington (C)	0.21	0.22	9%	±68%	146
Whitehorse (C)	0.38	0.25	-34%	±37%	239
Whittlesea (C)	0.24	0.34	37%	±45%	173
Wyndham (C)	0.24	0.44	80%	±43%	179
Yarra (C)	0.08	0.20	140%	±90%	146
Yarra Ranges (S)	0.50	0.37	-25%	±40%	188

Table 21 - Comparison of Modelled and VISTA07 Trip Rates by LGA (Secondary School Trips)

Average Household Trip Rate by Region
Home Based Education – Secondary | Re-estimated Zenith Model

Figure 28 - Comparison of Modelled and VISTA07 Trip Rates by Region (Secondary School Trips)

Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% CI	Sample
Inner City	0.09	0.16	87%	± 59%	377
Inner Suburbs	0.30	0.26	-13%	± 22%	813
Middle Suburbs	0.30	0.28	-9%	± 13%	2,328
Outer Suburbs	0.35	0.35	0%	± 13%	2,069
Major Regional Centre	0.29	0.27	-6%	± 27%	572
Regional	0.29	0.29	-1%	± 19%	1,069

Table 22 - Comparison of Modelled and VISTA07 Trip Rates by Region (Secondary School Trips)

Average Household Trip Rate by SD
Home Based Education – Secondary | Re-estimated Zenith Model

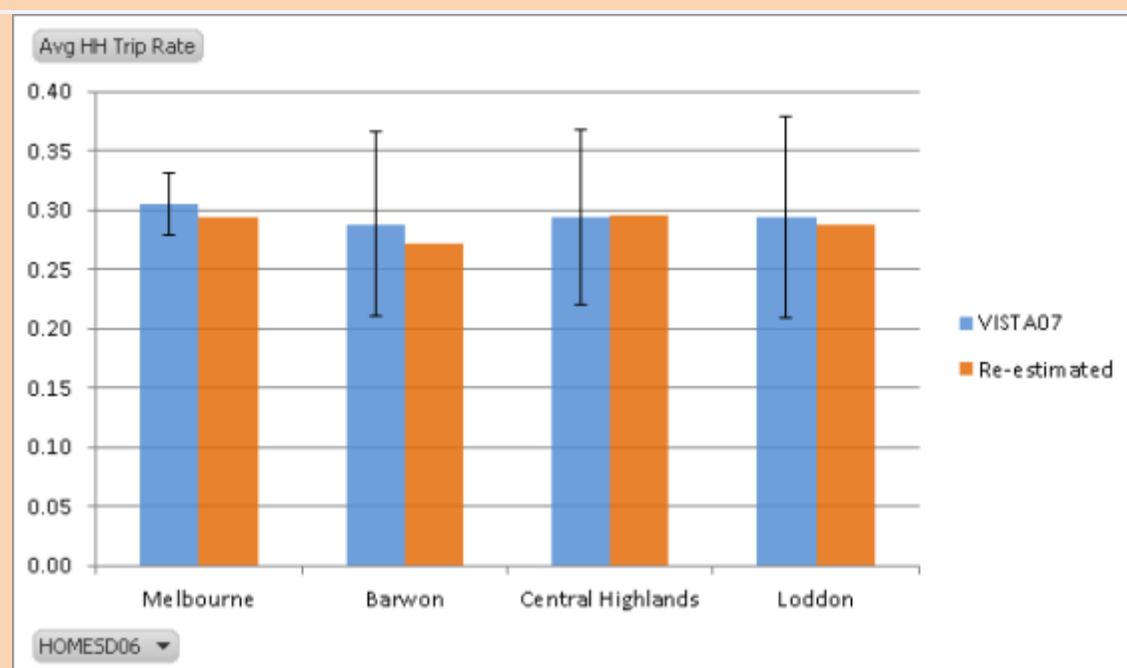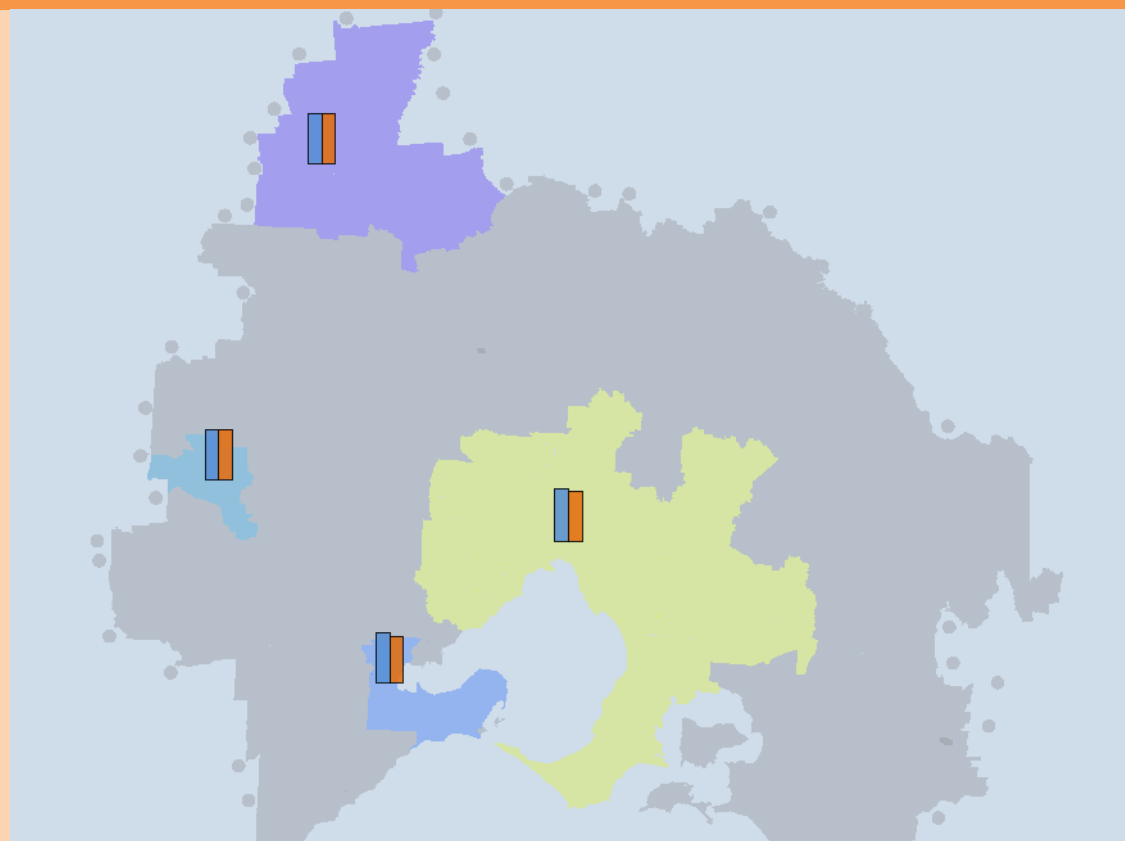*Figure 29 - Comparison of Modelled and VISTA07 Trip Rates by SD (Secondary School Trips)*

Avg HH Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.
Melbourne	0.31	0.30	-2%	± 9%
Barwon	0.29	0.28	-4%	± 27%
Central Highlands	0.29	0.30	2%	± 25%
Loddon	0.29	0.29	-1%	± 29%

Table 23 - Comparison of Modelled and VISTA07 Trip Rates by SD (Secondary School Trips)

5.5 Home Based Education – Tertiary

5.5.1 Travel Market

This section provides a high level analysis of the market for *Home Based Education – Tertiary,* which we will refer to as tertiary travel.

The breakdown of tertiary trips according to the Zenith classification is seen in Figure 30 below.
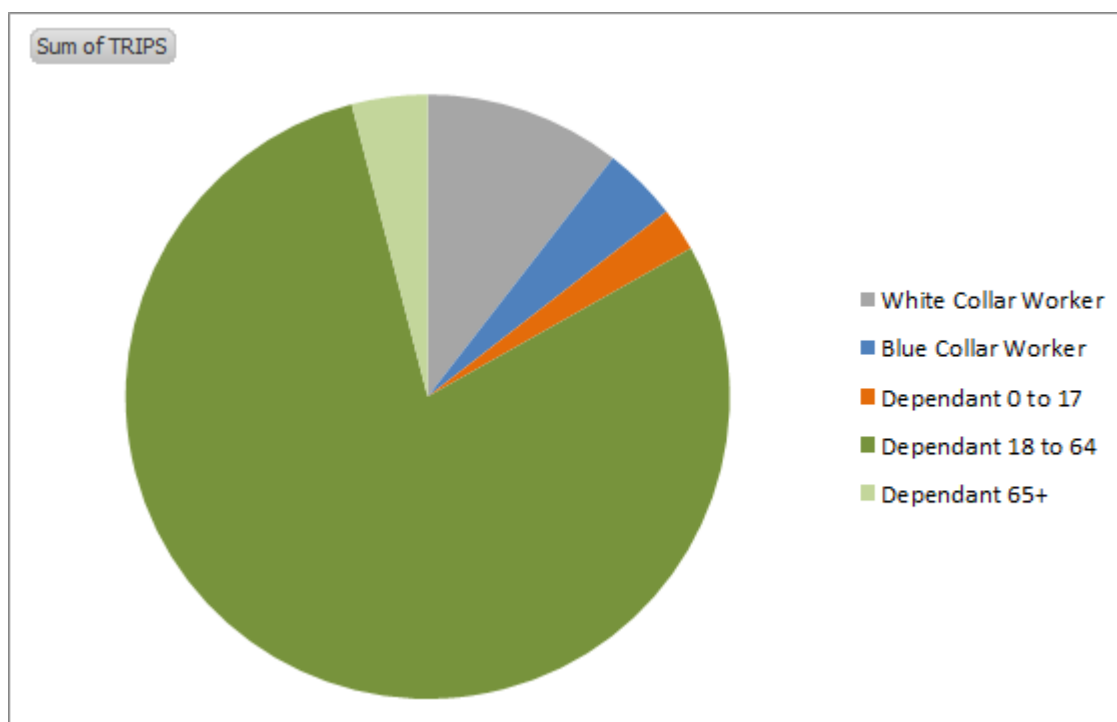
Figure 30 - The breakdown of Tertiary Trips by Zenith Variables

Approximately 79% of tertiary trips are made by dependants aged 18 to 64; of the remainder, 2% are made by dependants aged 0 to 17 (young university students and TAFE students), 4% are dependants aged 65 or greater, and 11% of trips are made by white collar workers, 4% of trips made by blue collar workers.

A further breakdown, shown in Figure 31 below, reveals that 67% of trips are by full time tertiary students, with another 11% enrolled in part time study.
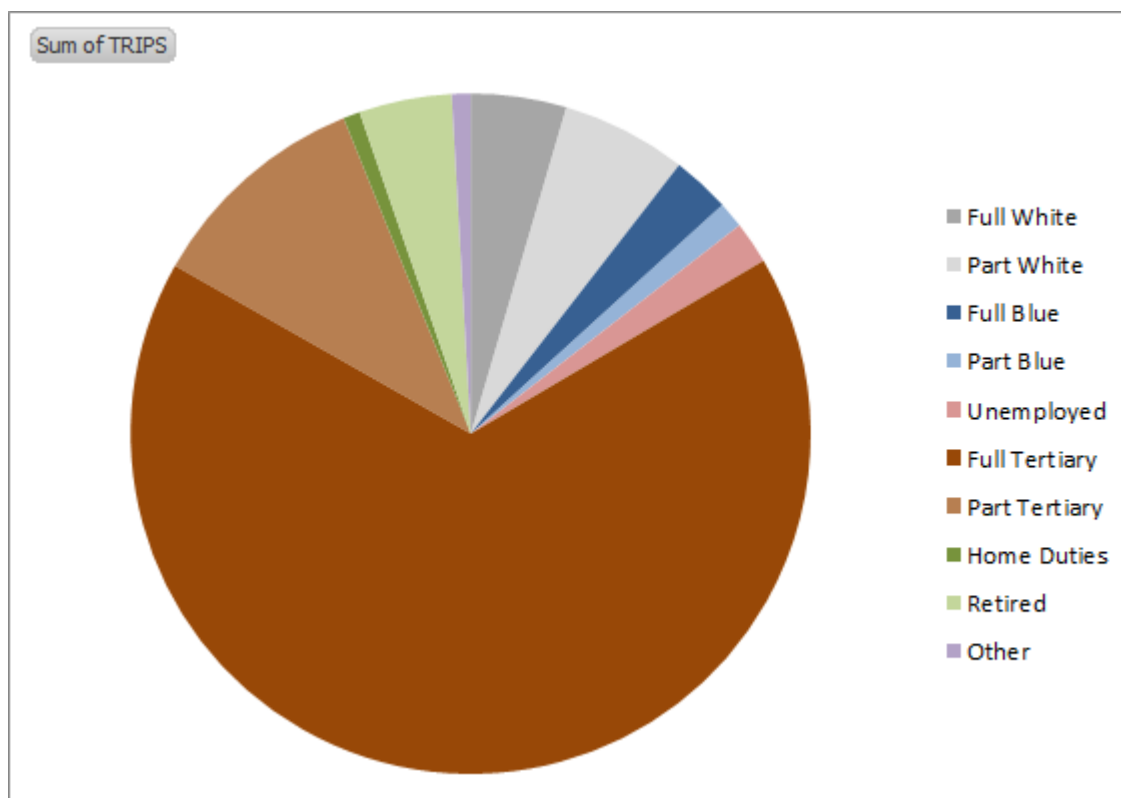
Figure 31 - The Breakdown of Tertiary Trips by Main Activity

The average trip rate per person for each of the Zenith person types is shown in Figure 32 below. On average, dependants aged 18 to 64 make 0.25 tertiary trips a day, while all other categories range from 0.01 to 0.02 trips per day.
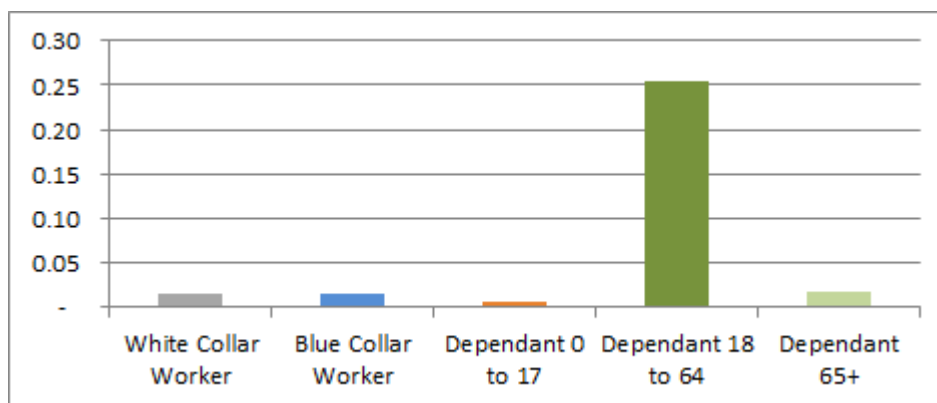
Figure 32 - Average Tertiary Trip Rate per Person by Zenith Variables

A clearer picture of tertiary education emerges if we group people by their Main Activity. As shown in Figure 33 below, full time tertiary students make 0.95 tertiary education trips per day, while part time students average approximately half that, at 0.47.
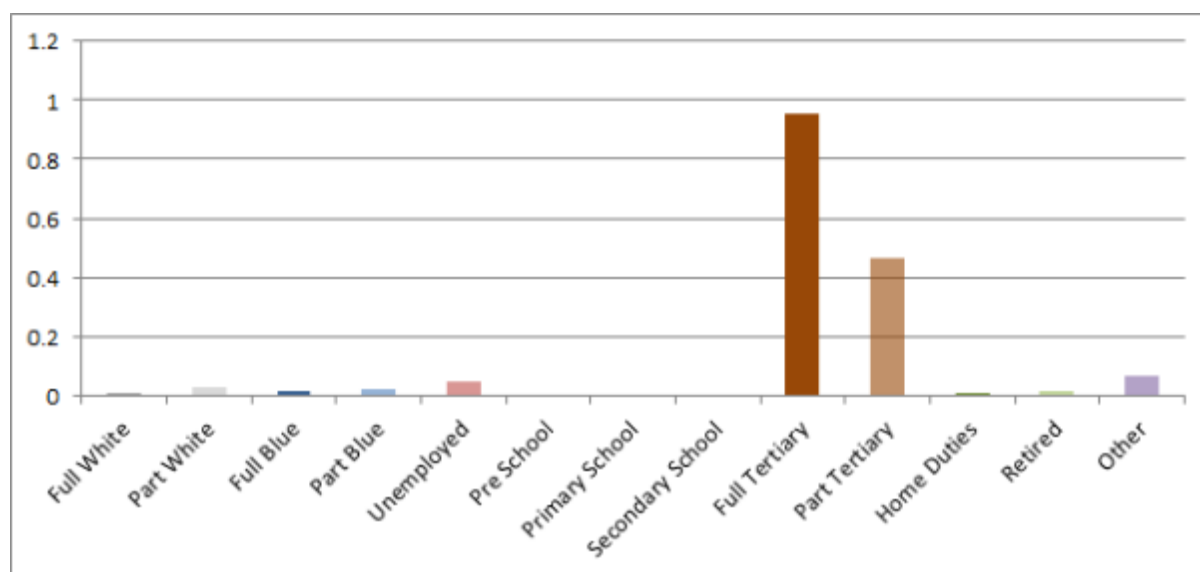
Figure 33 - Average Tertiary Trip Rate by Main Activity

5.5.2   Model Estimation

5.5.2.1   Parameter Estimates

The re-estimated model parameters for travel for tertiary education are presented in Table 24 below.

Parameter	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE	STANDARD ERROR
WHITEWORKERS_1	0.079	4.453	0.000	0.018
WHITEWORKERS_2	0.175	8.790	0.000	0.020
WHITEWORKERS_3+	0.249	5.577	0.000	0.045
BLUEWORKERS_1	0.067	3.523	0.000	0.019
BLUEWORKERS_2	0.106	2.490	0.013	0.042
BLUEWORKERS_3+	0.185	1.721	0.086	0.108
DEPS_18TO64_1	0.238	13.371	0.000	0.018
DEPS_18TO64_2	0.766	22.562	0.000	0.034
DEPS_18TO64_3+	1.203	15.279	0.000	0.079
CARS_0	-0.052	-1.626	0.107	0.032
CARS_1	-0.080	-4.989	0.000	0.016
CARS_2	-0.121	-6.860	0.000	0.018

Table 24 –Parameter Estimates and Properties for Tertiary Travel

The largest parameters are associated with households that have dependants aged 18-64, which is consistent with this group having the by far the highest trip rate for tertiary travel. Households with 1, 2 and 3+ dependants aged 18-64 have parameters of 0.238, 0.766, and 1.203 respectively.

White collar workers have a higher set of parameters than blue collar workers, which is interesting given that they have almost identical trip rates for tertiary education. It seems that having white collar worker(s) in a household increases the likelihood that any dependants in the household will

undertake tertiary studies (or, the opposition assertion could be made with respect to blue collar workers).

There is also an interesting relationship between car ownership and tertiary travel. Households with two cars are least likely (all other things being equal) of making tertiary trips (as indicated by the -0.121 parameter), while households with 3 or more cars are most likely (the absence of a 3+ parameter means that the parameter is zero). Put another way, there is a greater chance of a dependant aged 18 to 64 being a tertiary student if they live in a 3+ car household (relative to a 2 car household).

5.5.3   Model Validation

5.5.3.1   Demographic Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of demographic aggregation.

Referring to Table 25 below, it can be observed that:

- Tertiary trip rates are low for 1 and 2 person households, but jump significantly once the household size reaches 3. The increases in trip rate are more modest as the household increases to 4 and 5 people (the trip rate for 6 people may simply be an outlier, given the wide confidence interval),
- The tertiary trip rate increases slowly as household income increases, and is significantly higher for households in the highest income quintile.
- Tertiary trip rates are low for households with 2 or fewer cars, and increase sharply for households with 3 or more cars. Many tertiary students will own a car and live with their parents (who may both own a car). Upon completing their studies many will move out of home, leaving the household as a 2 car household. The model replicates this pattern closely (due partly to the inclusion of parameters on car ownership level).

Average Household Trip Rates by Household Characteristics
Home Based Education – Tertiary | Re-estimated Zenith Model
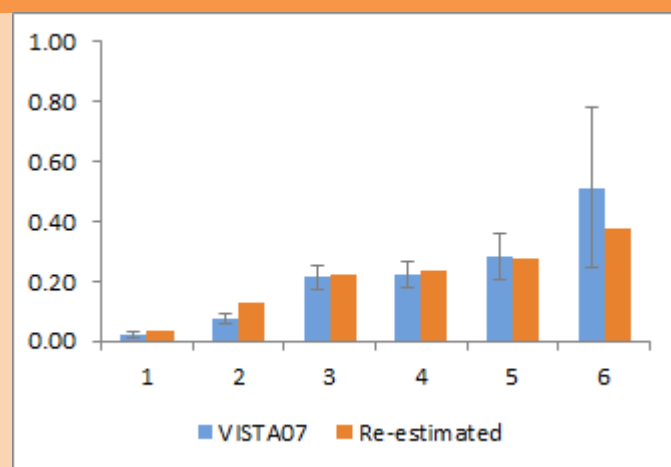
Household Size

Household Size	VISTA07	Re-estimated	Diff	95% C.I.	Sample
1	0.02	-0.01	-127%	± 47%	1,571
2	0.07	0.09	18%	± 23%	2,682
3	0.21	0.22	4%	± 20%	1,182
4	0.22	0.23	5%	± 19%	1,277
5	0.28	0.27	-3%	± 28%	392
6	0.51	0.39	-24%	± 52%	103

Household Income
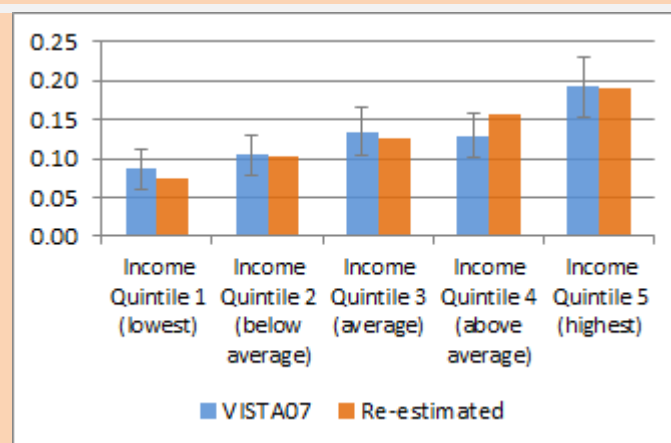
Income Quintile	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Income Quintile 1 (lowest)	0.09	0.07	-15%	± 30%	1,423
Income Quintile 2 (below average)	0.10	0.10	-3%	± 25%	1,409
Income Quintile 3 (average)	0.13	0.13	-7%	± 22%	1,467
Income Quintile 4 (above average)	0.13	0.16	22%	± 22%	1,441
Income Quintile 5 (highest)	0.19	0.19	-1%	± 20%	1,488
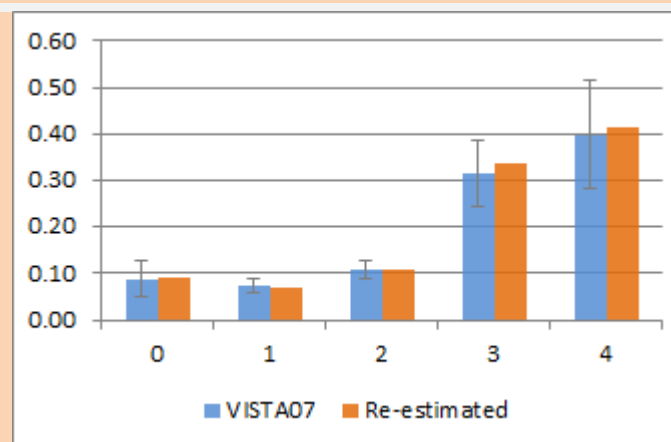
Cars Owned

Car Ownership	VISTA07	Re-estimated	Diff	95% C.I.	Sample
0	0.09	0.09	5%	± 43%	483
1	0.07	0.07	-4%	± 22%	2,614
2	0.11	0.11	0%	± 17%	3,105
3	0.31	0.34	7%	± 22%	745
4	0.40	0.42	4%	± 29%	225

Table 25 - Validation by Demographic Categories (Tertiary Trips)

5.5.3.2 Spatial Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of spatial aggregation.

Referring to the LGA analysis (Figure 34 and Table 26), it can be observed that:

- There is a great deal of variation in the surveyed average trip rates for the LGAs. While some of this variation will be due to real spatial differences, much of it will be due to random variation in the sample (as indicated by the wide error bars).
- The re-estimated model is unable to predict the differences between sampled LGAs. With each sample consisting of an average of 213 households, and with 18 – 64 being such a wide age band, it is an unsurprising (but still unsatisfying!) result.
- To improve the accuracy of the model at this disaggregate level, we would need to specifically include the age groups or main activities which drive tertiary travel.

Moving to the Concentric Ring analysis (Figure 35 and Table 27), it can be observed that:

- Tertiary trip rates are highest in the inner and middle suburbs (the inner city is also known to contain many international students, but these were largely missed in VISTA).
- The model largely misses this trend, with the modelled predictions hovering around the average.

At the SD level (Figure 36 and Table 28), the model has a tendency to over-estimate the regional SDs of Barwon, the Central Highlands and Loddon, and under-estimate Melbourne.

It can be concluded that until we include tertiary students as a separate category (or at least further disaggregate the 18-64 age group) the model will tend to predict a fairly uniform average tertiary trip rate across the modelled area, and capture only a small amount of spatial variation.

Average Household Trip Rate by LGA
Home Based Education – Tertiary | Re-estimated Zenith Model
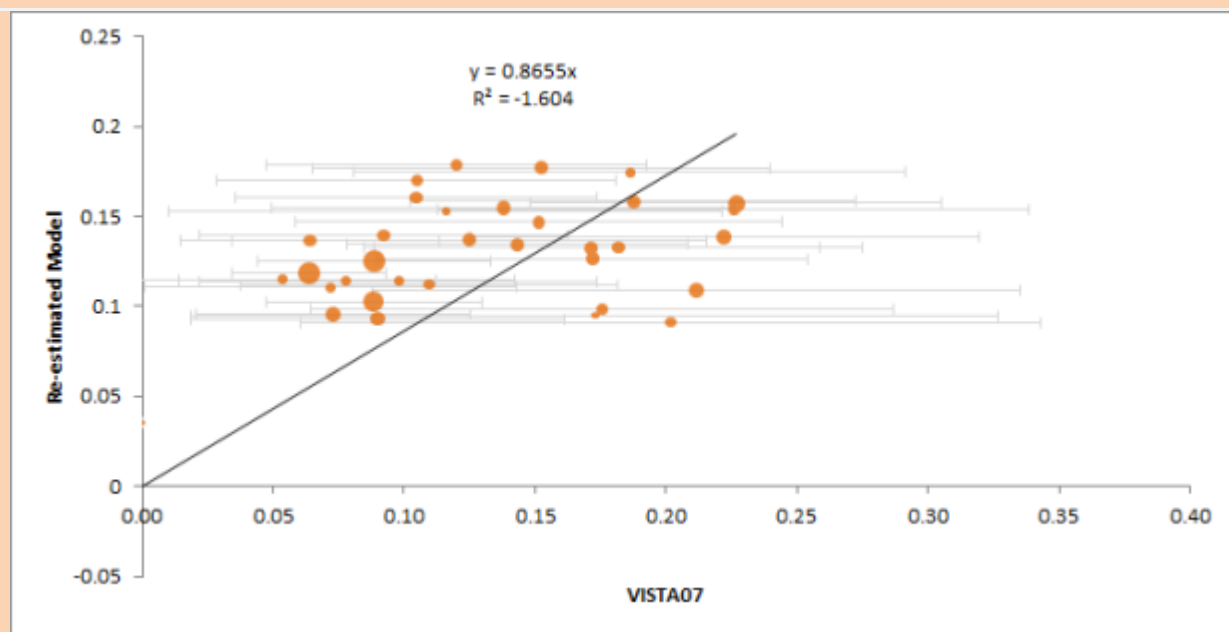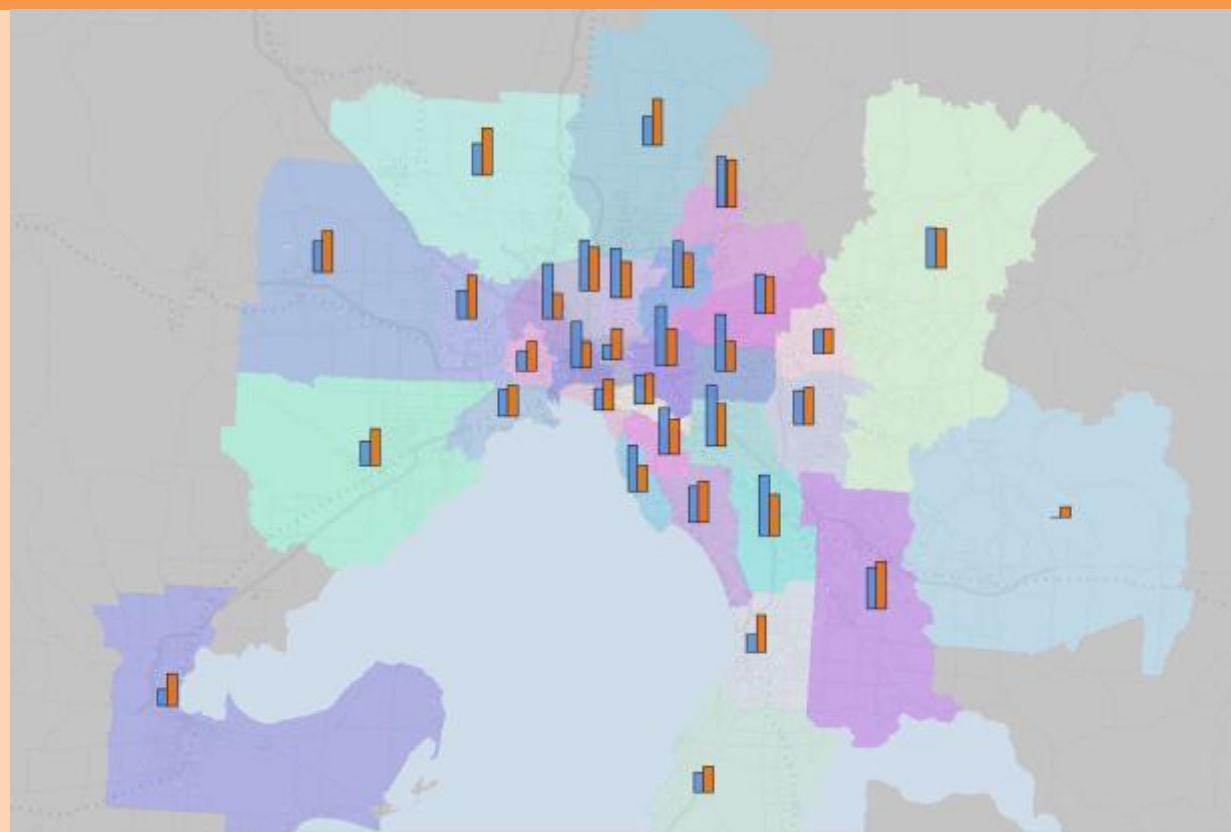
Figure 34 – Comparison of Modelled and VISTA07 Trip Rates by LGA (Tertiary Education Trips)

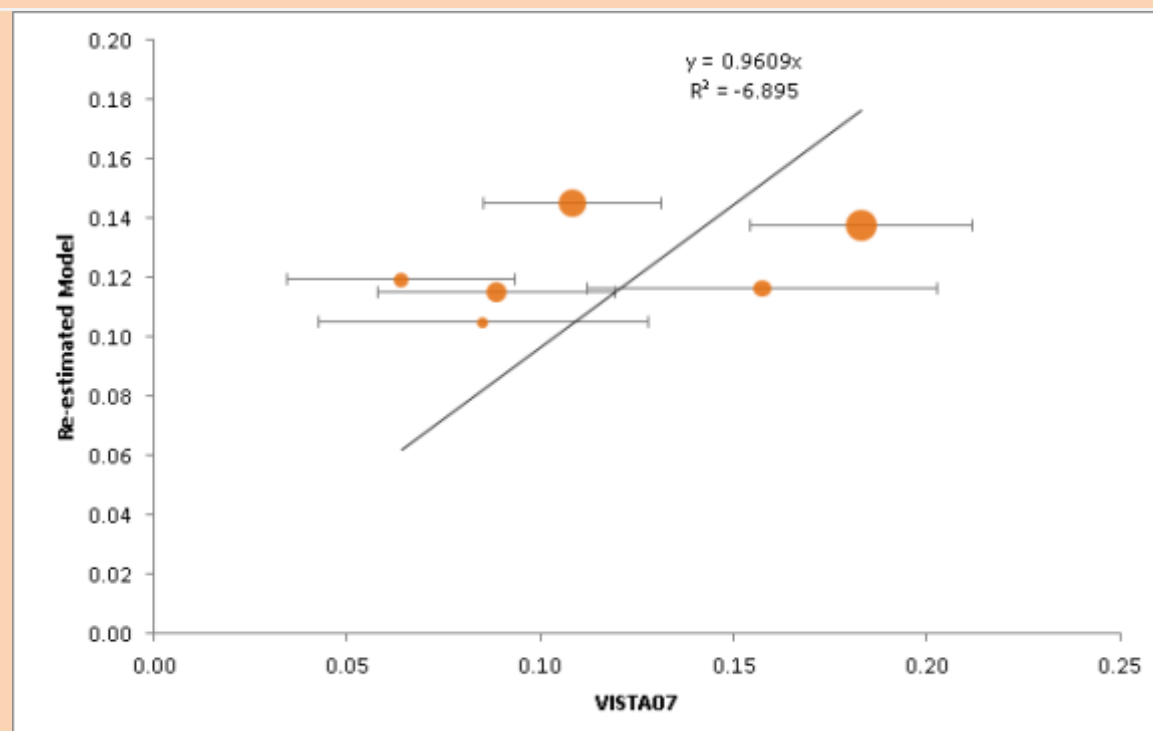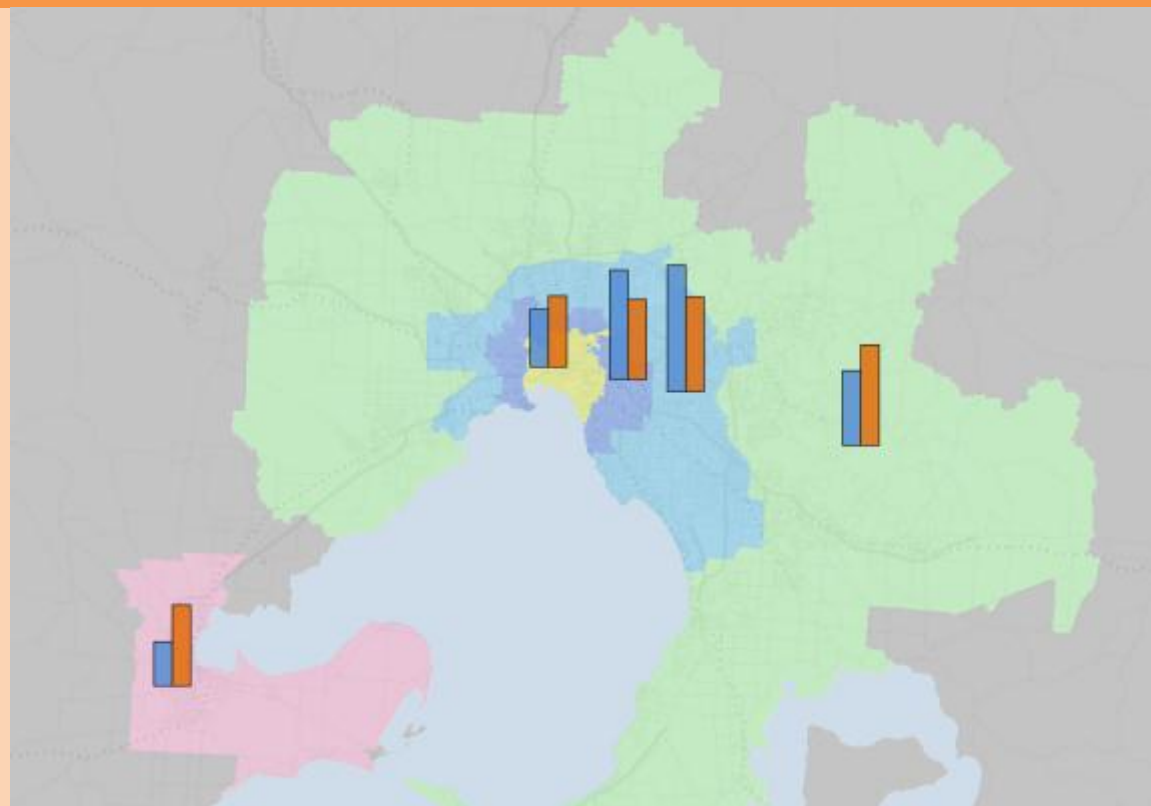| Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Ballarat (C)	0.09	0.13	41%	±50%	581
Banyule (C)	0.17	0.13	-26%	±48%	240
Bayside (C)	0.18	0.10	-44%	±63%	153
Boroondara (C)	0.22	0.14	-38%	±44%	265
Brimbank (C)	0.10	0.16	54%	±66%	171
Cardinia (S)	0.00	0.04	NA	NA	32
Casey (C)	0.15	0.18	16%	±57%	220
Darebin (C)	0.18	0.13	-27%	±51%	194
Frankston (C)	0.06	0.14	113%	±77%	181
Glen Eira (C)	0.17	0.13	-23%	±51%	197
Greater Bendigo (C)	0.09	0.10	16%	±47%	488
Greater Dandenong (C)	0.23	0.15	-32%	±50%	167
Greater Geelong (C)	0.06	0.12	86%	±46%	572
Hobsons Bay (C)	0.10	0.11	16%	±77%	128
Hume (C)	0.12	0.18	49%	±60%	189
Kingston (C)	0.14	0.15	12%	±64%	225
Knox (C)	0.12	0.14	10%	±72%	223
Manningham (C)	0.14	0.13	-6%	±46%	242
Maribyrnong (C)	0.07	0.11	54%	±99%	104
Maroondah (C)	0.09	0.09	3%	±79%	225
Melbourne (C)	0.17	0.09	-45%	±89%	62
Melton (S)	0.12	0.15	32%	±91%	88
Monash (C)	0.23	0.16	-31%	±35%	326
Moonee Valley (C)	0.20	0.09	-55%	±70%	153
Moreland (C)	0.19	0.16	-16%	±45%	239
Mornington Peninsula (S)	0.07	0.10	31%	±72%	251
Nillumbik (S)	0.19	0.17	-6%	±56%	112
Port Phillip (C)	0.08	0.11	47%	±82%	129
Stonnington (C)	0.11	0.11	3%	±66%	146
Whitehorse (C)	0.21	0.11	-48%	±58%	239
Whittlesea (C)	0.10	0.17	63%	±73%	173
Wyndham (C)	0.09	0.14	51%	±76%	179
Yarra (C)	0.05	0.12	115%	±109%	146
Yarra Ranges (S)	0.15	0.15	-3%	±61%	188

Table 26 - Comparison of Modelled and VISTA07 Trip Rates by LGA (Tertiary Trips)

Average Household Trip Rate by Region
Home Based Education – Tertiary | Re-estimated Zenith Model

Figure 35 - Comparison of Modelled and VISTA07 Trip Rates by Region (Tertiary Trips)

Avg Household Trip Rate	VISTA07	Re-estimated	Diff	95% CI	Sample
Inner City	0.09	0.10	23%	± 50%	377
Inner Suburbs	0.16	0.12	-26%	± 29%	813
Middle Suburbs	0.18	0.14	-25%	± 16%	2,328
Outer Suburbs	0.11	0.14	34%	± 21%	2,069
Major Regional Centre	0.06	0.12	86%	± 46%	572
Regional	0.09	0.11	29%	± 35%	1,069

Table 27 - Comparison of Modelled and VISTA07 Trip Rates by Region (Tertiary Trips)

Average Household Trip Rate by SD
Home Based Education – Tertiary | Re-estimated Zenith Model
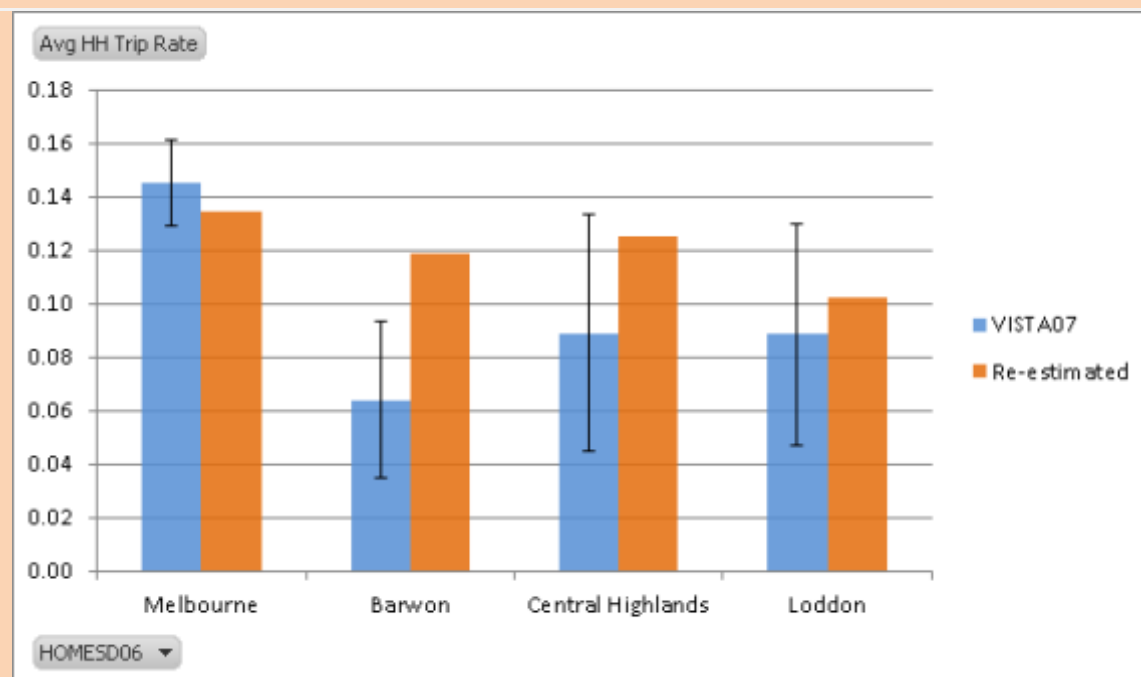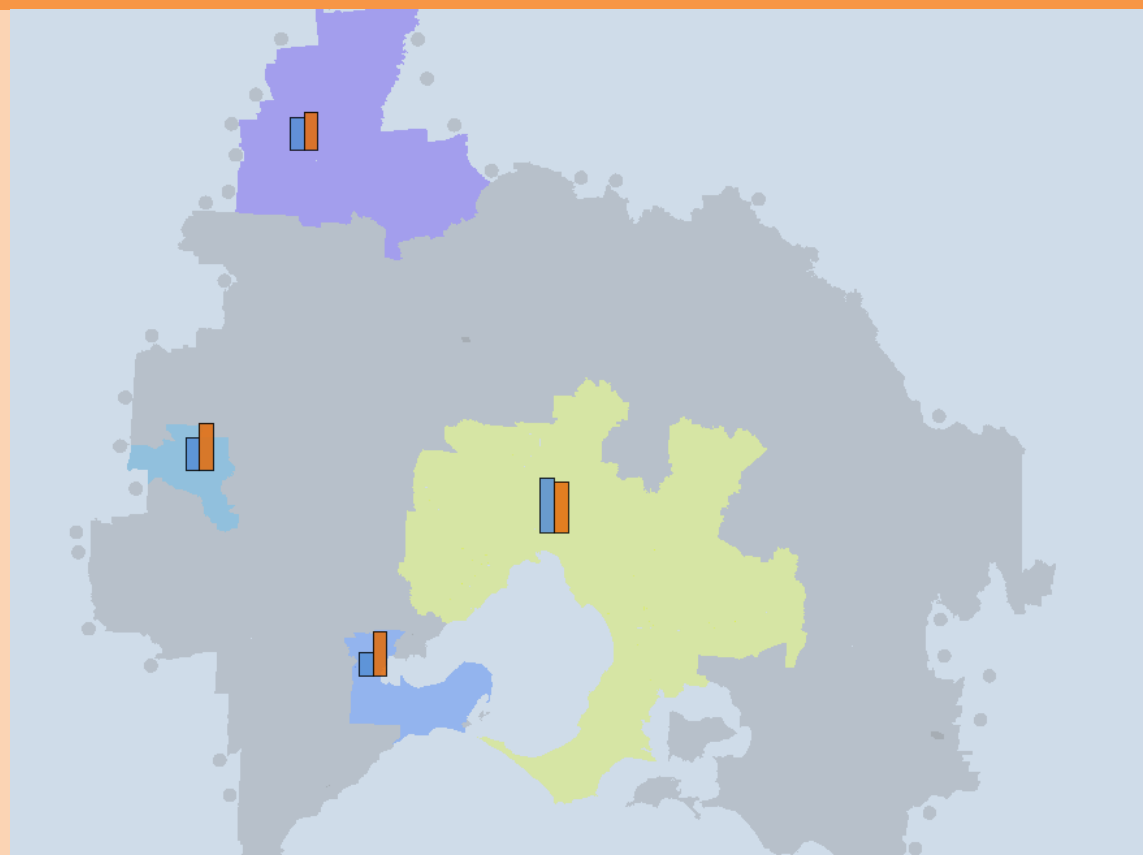
Figure 36 - Comparison of Modelled and VISTA07 Trip Rates by SD (Tertiary Trips)

Avg HH Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.
Melbourne	0.15	0.13	-7%	±11%
Barwon	0.06	0.12	86%	±46%
Central Highlands	0.09	0.13	41%	±50%
Loddon	0.09	0.10	16%	±47%

Table 28 - Comparison of Modelled and VISTA07 Trip Rates by SD (Tertiary Trips)

5.6 Home Based Shopping

5.6.1 Travel Market

This section provides a high level analysis of the market for *Home Based Shopping and Personal Business*, which we will refer to simply as shopping.

The breakdown of shopping trips according to the Zenith person classification is seen in Figure 37 below.
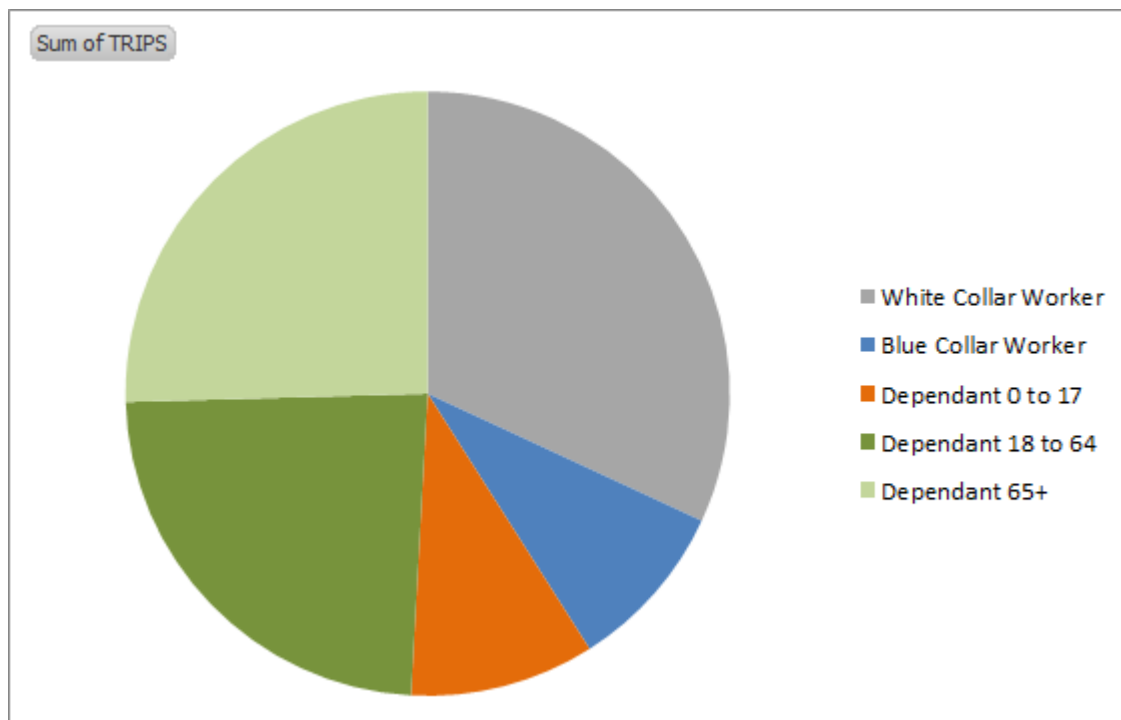
Figure 37 - The breakdown of Shopping Trips by Zenith Variables

White collar workers comprise 32% of the market, with dependants 18 to 64 and dependants 65+ each making up around 25%. The remainder is evenly split between blue collar workers and dependants.

The breakdown with respect to main activities is presented in Figure 38.
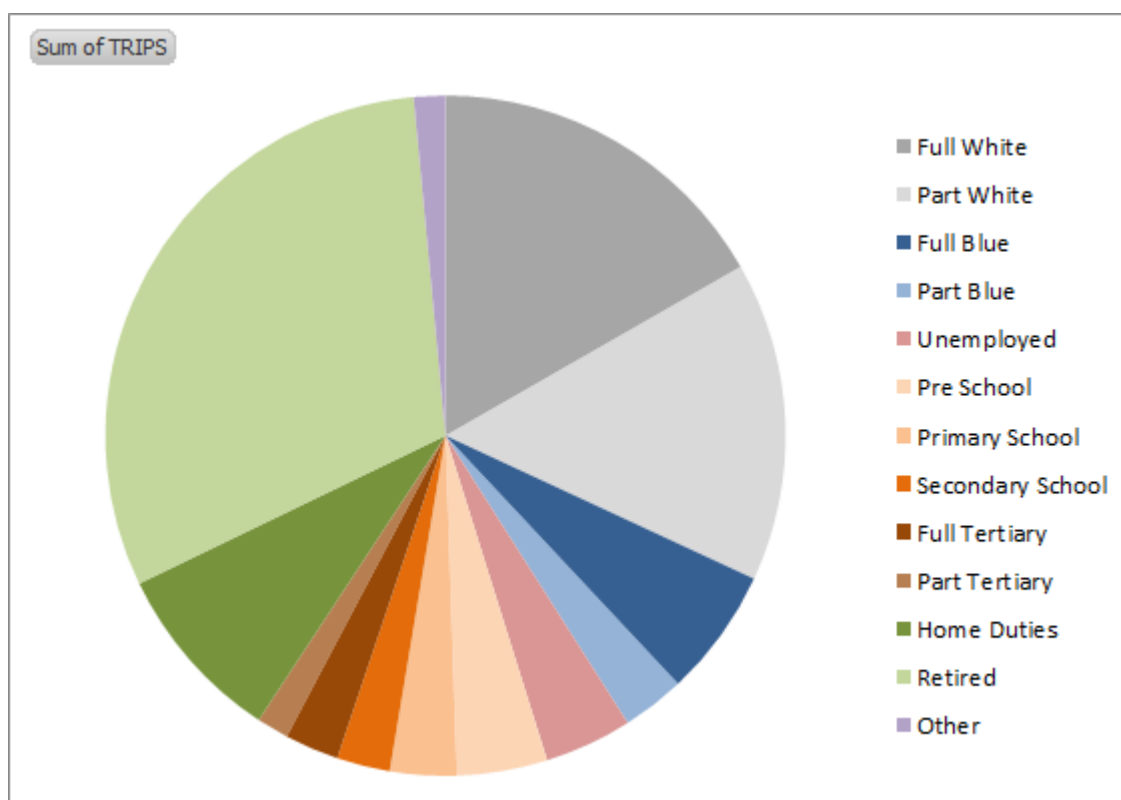
Figure 38 - The Breakdown of Shopping Trips by Main Activity

Perhaps of more interest is the average trip rate per person for each person type. Referring to Figure 39 below, it can be seen that dependants aged 65+ are by far the most frequent makers of home based shopping trips, averaging just over 1.2 per day (equivalent to 0.6 return trips). Dependants aged 18 to 64 are the next highest, with 0.86, while white and blue collar workers average 0.5 and 0.4 shopping trips per day respectively.
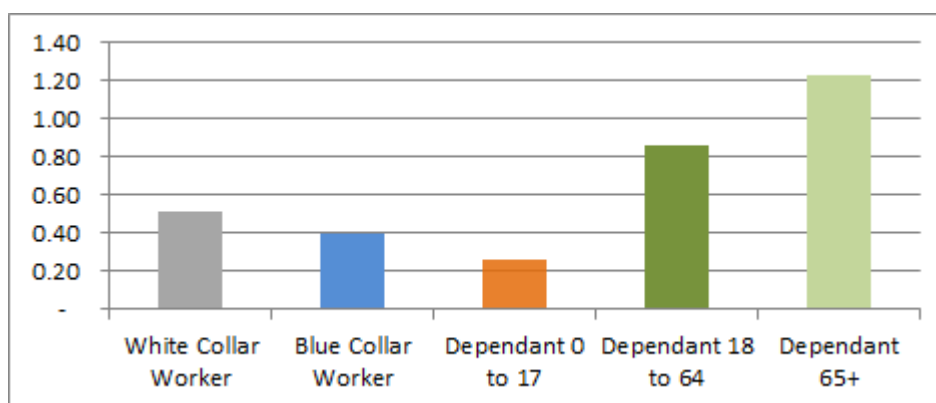
Figure 39 - Average Shopping Trip Rate per Person by Zenith Variables

The differences in shopping trip rates are even greater if we group people according to their main activity, as seen in Figure 40 below. Retirees (and other) are the most frequent makers of home based shopping trips, with the unemployed, and people engaged in home duties (but not in the labour force) the next most frequent.

It is also interesting to note the stark differences between those engaged in full or part time work or study. The trip rate for part time white collar workers is double that of their full time counterparts

(0.78 versus 0.39), with a similar (but slightly weaker) pattern existing for blue collar workers and tertiary students. Primary and secondary school students are by far the least likely to make home based shopping trips, averaging 0.2 trips per day.
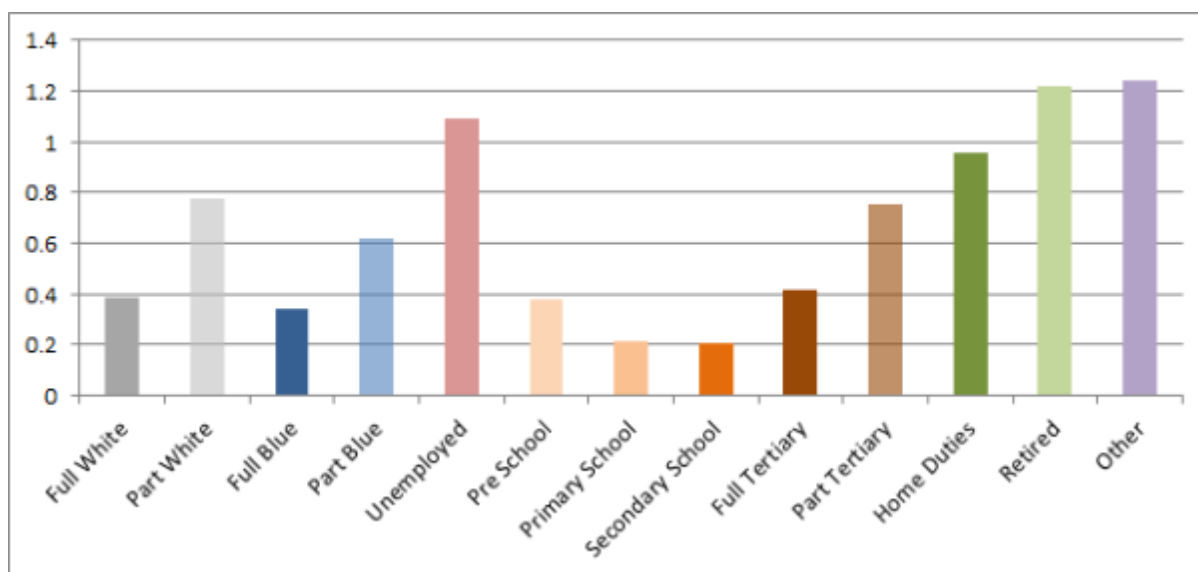
Figure 40 - Average Shopping Trip Rate by Main Activity

5.6.2   Model Estimation

5.6.2.1   Parameter Estimates

The re-estimated model parameters for home based shopping are presented in Table 29 below.

Parameter	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE	STANDARD ERROR
WHITEWORKERS_1	0.161	2.135	0.034	0.076
WHITEWORKERS_2+	0.324	3.491	0.001	0.093
DEPS_0TO17_1	0.252	2.992	0.003	0.084
DEPS_0TO17_2	0.399	4.783	0.000	0.083
DEPS_0TO17_3+	0.468	3.803	0.000	0.123
DEPS_18TO64_1	0.524	7.660	0.000	0.068
DEPS_18TO64_2	1.104	8.895	0.000	0.124
DEPS_18TO64_3+	1.639	5.874	0.000	0.279
DEPS_65PLUS_1	0.715	7.693	0.000	0.093
DEPS_65PLUS_2+	1.799	15.395	0.000	0.117
CARS_1	0.379	3.287	0.001	0.115
CARS_2	0.482	4.024	0.000	0.120
CARS_3+	0.830	6.130	0.000	0.135
constant	0.254	2.100	0.037	0.121

Table 29 –Parameter Estimates and Properties for Shopping Travel

Reflecting the broad mix of people who undertake shopping trips, there are statistically significant parameters for all person types except blue collar workers (which have parameter zero). In addition, a household constant (of 0.254) was found to be statistically significant (unlike other trip purposes). The presence of a constant is reflective of the universal need to shop among all household types.

Dependants aged 65+ have the highest parameters: 0.715 and 1.799 for households with 1 and 2+ such dependants respectively. This group also had the highest trip rate.

Dependants aged 18 to 64 have the next highest parameters: 0.524, 1.104 and 1.639 for 1, 2 and 3+ such dependants respectively.

Interestingly, the presence of dependants aged 0 to 17 is the next largest influence, with parameters of 0.252, 0.399 and 0.469 for 1, 2, and 3+ such dependants respectively. While these dependants will indeed make some shopping trips, they are also likely to stimulate shopping trips in their parents.

Car ownership also has a strong influence on shopping trip rates, with parameters of 0.379, 0.482 and 0.83 for households with 1, 2 and 3+ cars (households with no car have a parameter of zero). Therefore, on average, a household with 1 car will make 0.379 more shopping trips than a household with 0 cars, all other things being equal.

5.6.3 Model Validation

5.6.3.1 Demographic Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of demographic aggregation.

Referring to Table 30 below, it can be observed that:

- While 1 person households make noticeably less shopping trips, the shopping trip rate is fairly stable across household sizes. The re-estimated model is fairly successful in replicating this pattern, though it does slightly under-predict the trip rate of 2 and 3 person households, and over-predict the trip rate for 4 and 5 person households.
- The number of shopping trips is generally uniform across all income groups,
- The number of shopping trips increases with the number of cars owned by the household. It is noteworthy that car ownership is more closely correlated with shopping trips than household size.

Average Household Trip Rates by Household Characteristics
Home Based Shopping | Re-estimated Zenith Model
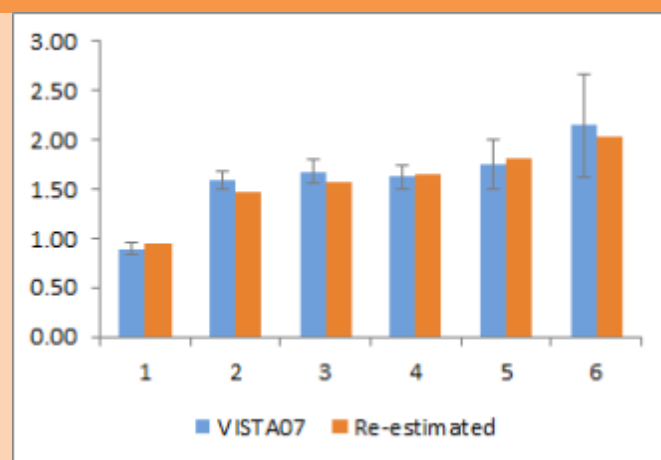
Household Size

Household Size	VISTA07	Re-estimated	Diff	95% C.I.	Sample
1	0.90	0.94	5%	± 7%	1,571
2	1.59	1.46	-8%	± 5%	2,682
3	1.68	1.57	-6%	± 7%	1,182
4	1.63	1.65	1%	± 7%	1,277
5	1.75	1.80	3%	± 14%	392
6	2.14	2.04	-5%	± 24%	103

Household Income
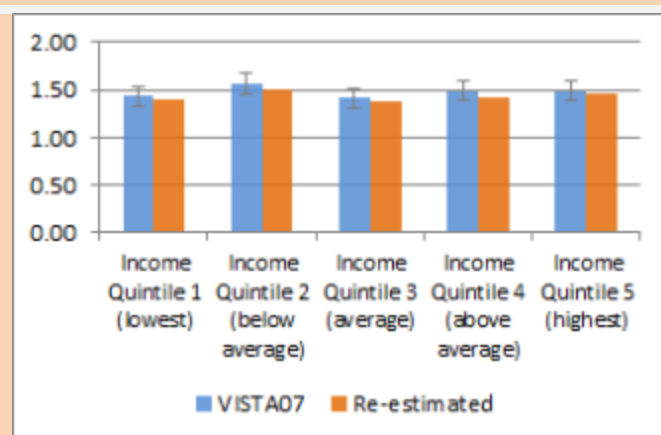
Income Quintile	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Income Quintile 1 (lowest)	1.43	1.39	-3%	± 7%	1,423
Income Quintile 2 (below average)	1.57	1.51	-4%	± 7%	1,409
Income Quintile 3 (average)	1.42	1.37	-3%	± 7%	1,467
Income Quintile 4 (above average)	1.49	1.42	-5%	± 7%	1,441
Income Quintile 5 (highest)	1.48	1.45	-2%	± 7%	1,488
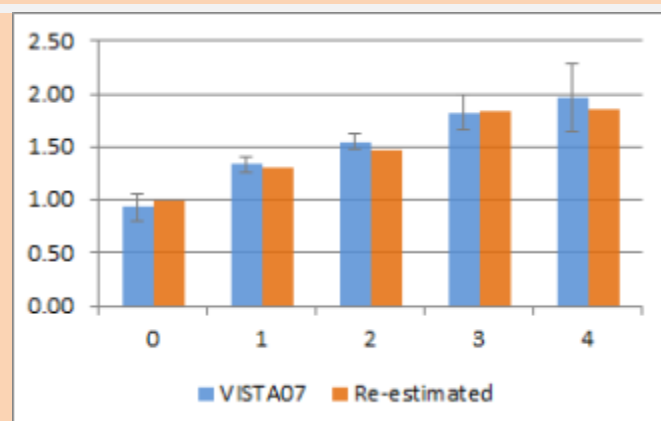
Cars Owned

Car Ownership	VISTA07	Re-estimated	Diff	95% C.I.	Sample
0	0.93	0.99	7%	± 14%	483
1	1.34	1.30	-3%	± 5%	2,614
2	1.55	1.46	-6%	± 5%	3,105
3	1.82	1.83	0%	± 9%	745
4	1.96	1.85	-6%	± 16%	225

Table 30 - Validation by Demographic Categories (Shopping Trips)

5.6.3.2 Spatial Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of spatial aggregation.

Referring to the LGA analysis (Figure 41 and Table 31), it can be observed that:

- Home based shopping trip rates are fairly uniform across Melbourne, with an average of around 1.5 trips per household,
- The model is not able to explain much (if any) variation which occurs at the LGA level. The modelled predictions tend to hover around 1.4 – 1.5 trips per day. This isn't to say that the model is necessarily wrong; with an average sample size of 213 households per LGA, there is considerable uncertainty in the surveyed trip rates. As such, we think that most of the variation at the LGA level is due to sampling.

Sample size issues are less likely to play a role at the more aggregate Concentric Ring level. Referring to Figure 42 and Table 32, it can be seen that:

- Trip rates increase from 1.17 in the Inner City to 1.56 in the middle suburbs of Melbourne, but then drop to 1.36 in the outer suburbs. This may be due to a lack of high streets in the outer suburbs, in which case accessibility to shops may play a role. (does anyone agree??? Thoughts?). It is encouraging to note that at this level, the model is quite successful in replicating the observed pattern (though it over-predicts trips in the outer suburbs).

At the SD level (Figure 43 and Table 33), it can be observed that:

- The model tends to predict a fairly even trip rate of around 1.45,
- The survey suggests that the Barwon SD has a significantly higher trip rate (1.76 trips per day; only a single LGA had a higher average trip rate: Bayside). Explanations are welcome!
- The survey also indicates that the regional SDs of the Central Highlands and Loddon have slightly higher trip rates than Melbourne, at 1.52 and 1.55, compared with 1.44 for Melbourne.

Average Household Trip Rate by LGA
Home Based Shopping | Re-estimated Zenith Model

$y = 0.9641x$
$R^2 = -1.824$
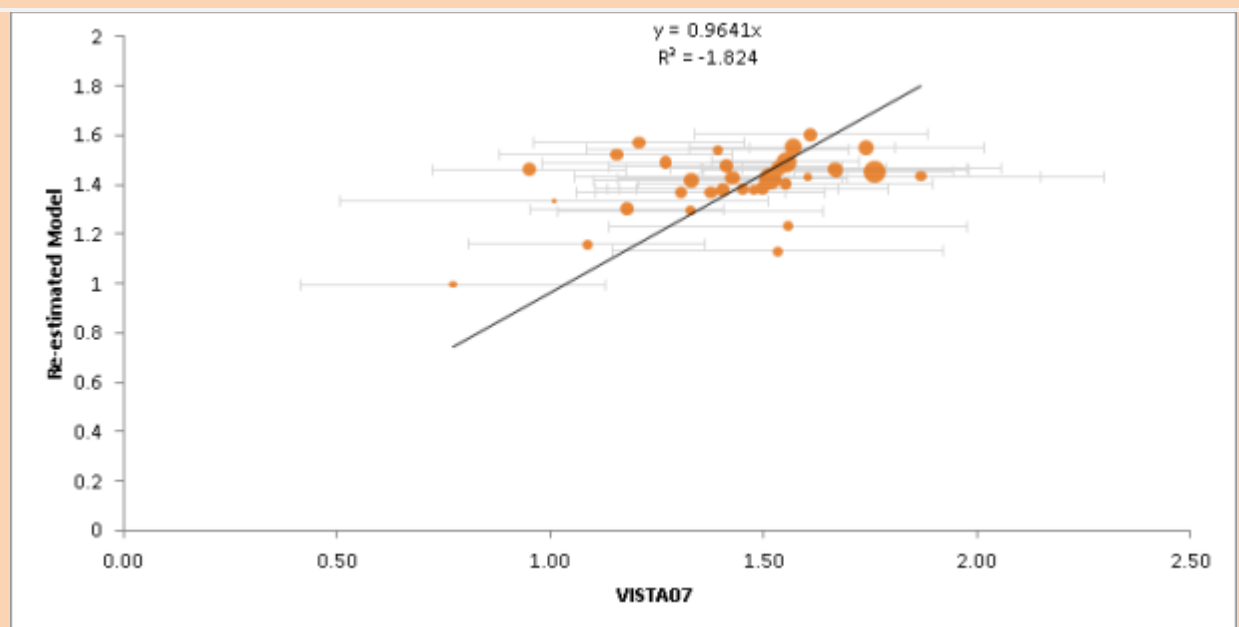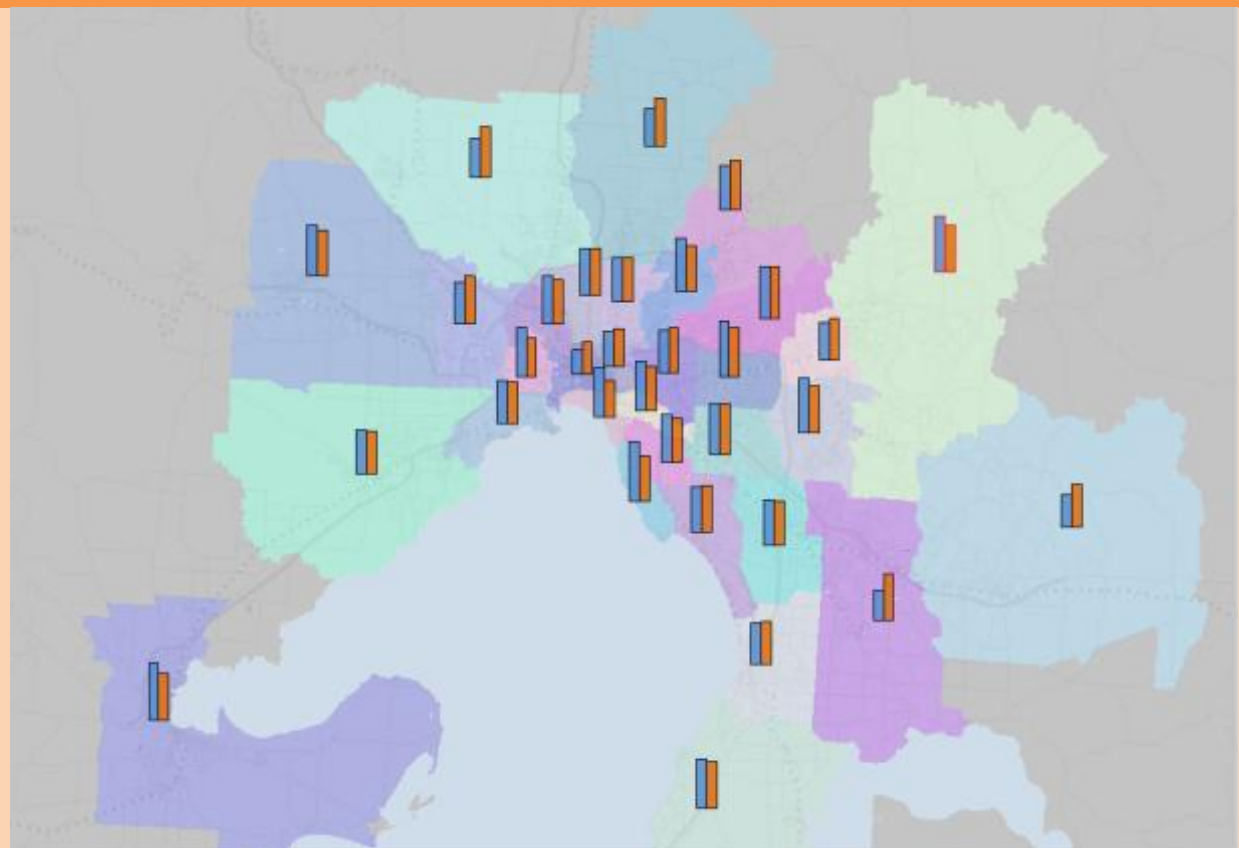
Figure 41 – Comparison of Modelled and VISTA07 Trip Rates by LGA (Shopping Trips)

Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Ballarat (C)	1.52	1.43	-6%	±11%	581
Banyule (C)	1.67	1.46	-13%	±19%	240
Bayside (C)	1.87	1.43	-23%	±23%	153
Boroondara (C)	1.33	1.42	6%	±17%	265
Brimbank (C)	1.27	1.49	17%	±23%	171
Cardinia (S)	1.01	1.34	32%	±50%	32
Casey (C)	0.95	1.46	54%	±24%	220
Darebin (C)	1.40	1.38	-2%	±19%	194
Frankston (C)	1.31	1.37	5%	±19%	181
Glen Eira (C)	1.50	1.38	-8%	±20%	197
Greater Bendigo (C)	1.55	1.49	-4%	±11%	488
Greater Dandenong (C)	1.45	1.39	-4%	±24%	167
Greater Geelong (C)	1.76	1.45	-17%	±11%	572
Hobsons Bay (C)	1.33	1.30	-2%	±23%	128
Hume (C)	1.21	1.57	30%	±21%	189
Kingston (C)	1.41	1.48	5%	±19%	225
Knox (C)	1.67	1.46	-12%	±19%	223
Manningham (C)	1.61	1.60	-1%	±17%	242
Maribyrnong (C)	1.56	1.23	-21%	±27%	104
Maroondah (C)	1.18	1.30	10%	±19%	225
Melbourne (C)	0.77	1.00	29%	±46%	62
Melton (S)	1.60	1.43	-11%	±34%	88
Monash (C)	1.57	1.55	-1%	±15%	326
Moonee Valley (C)	1.48	1.38	-7%	±21%	153
Moreland (C)	1.43	1.43	0%	±19%	239
Mornington Peninsula (S)	1.54	1.47	-4%	±16%	251
Nillumbik (S)	1.39	1.54	11%	±22%	112
Port Phillip (C)	1.53	1.13	-26%	±25%	129
Stonnington (C)	1.55	1.40	-10%	±22%	146
Whitehorse (C)	1.74	1.55	-11%	±16%	239
Whittlesea (C)	1.16	1.52	32%	±24%	173
Wyndham (C)	1.38	1.37	-1%	±20%	179
Yarra (C)	1.09	1.16	6%	±25%	146
Yarra Ranges (S)	1.75	1.47	-17%	±17%	188

Table 31 - Comparison of Modelled and VISTA07 Trip Rates by LGA (Shopping Trips)

Average Household Trip Rate by Region
Home Based Shopping | Re-estimated Zenith Model

Figure 42 - Comparison of Modelled and VISTA07 Trip Rates by Region (Shopping Trips)
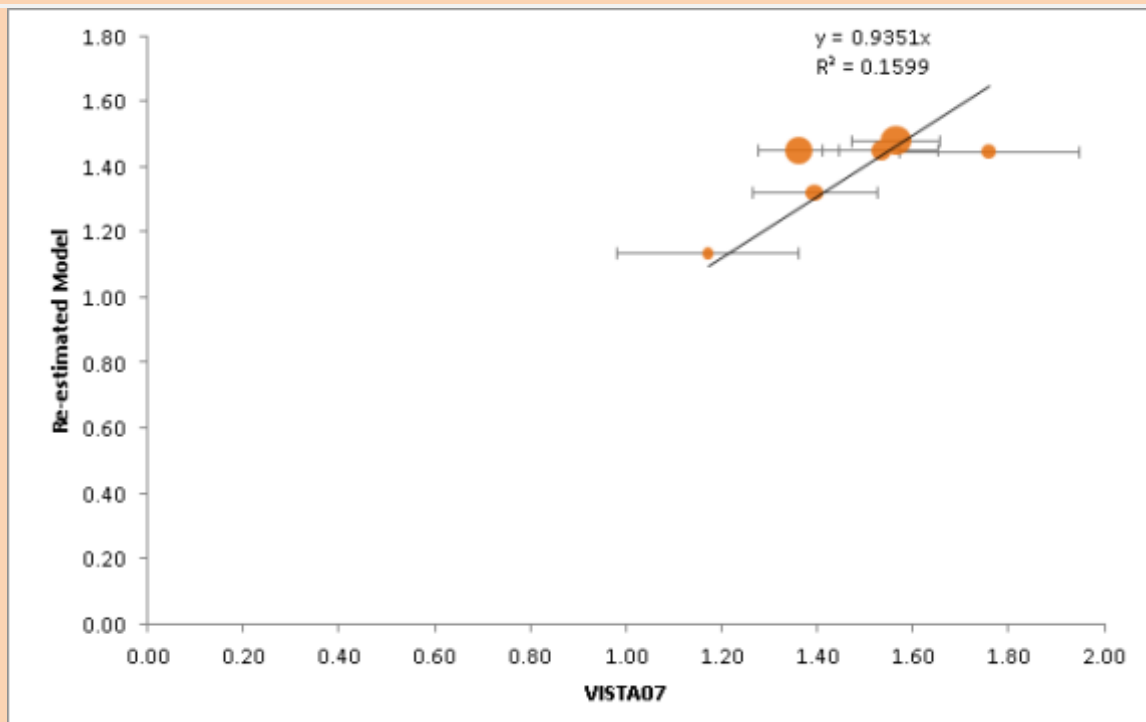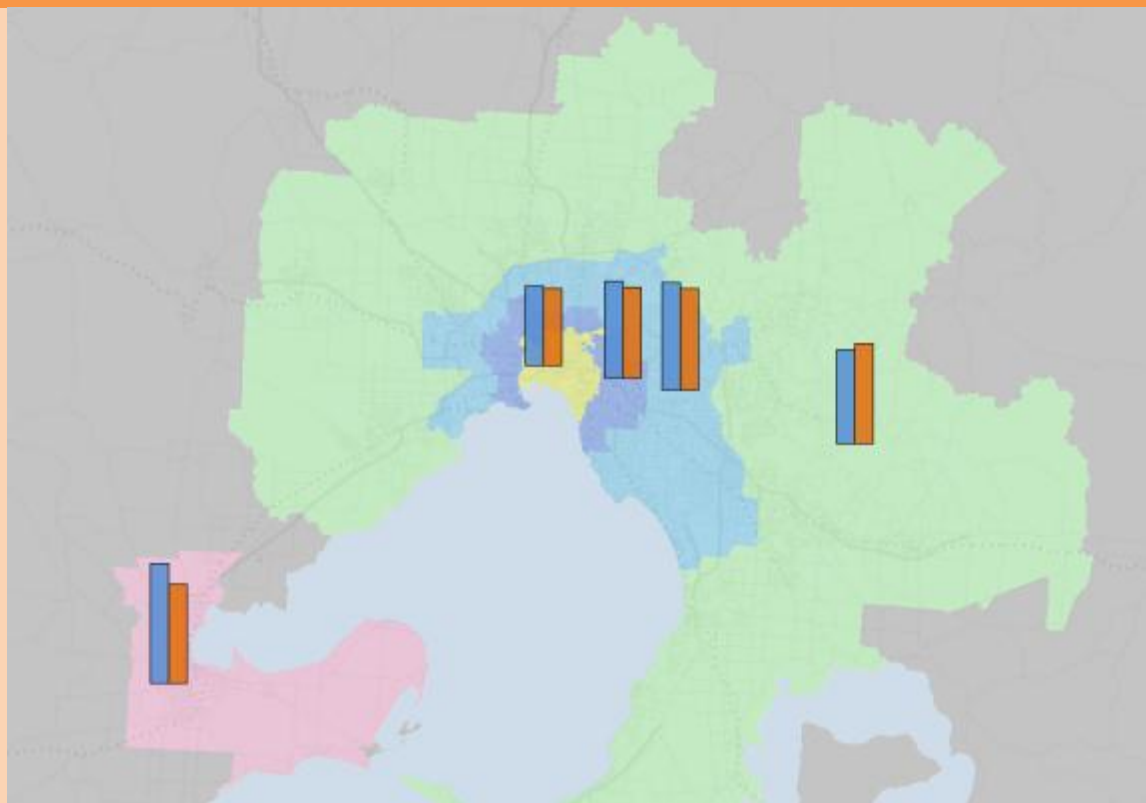
Avg Household Trip Rate	VISTA07	Re-estimated	Diff	95% CI	Sample
Inner City	1.17	1.13	-3%	± 16%	377
Inner Suburbs	1.39	1.32	-5%	± 9%	813
Middle Suburbs	1.56	1.48	-6%	± 6%	2,328
Outer Suburbs	1.36	1.45	6%	± 6%	2,069
Major Regional Centre	1.76	1.44	-18%	± 11%	572
Regional	1.533	1.449	-5%	± 8%	1,069

Table 32 - Comparison of Modelled and VISTA07 Trip Rates by Region (Shopping Trips)

Average Household Trip Rate by SD
Home Based Shopping | Re-estimated Zenith Model
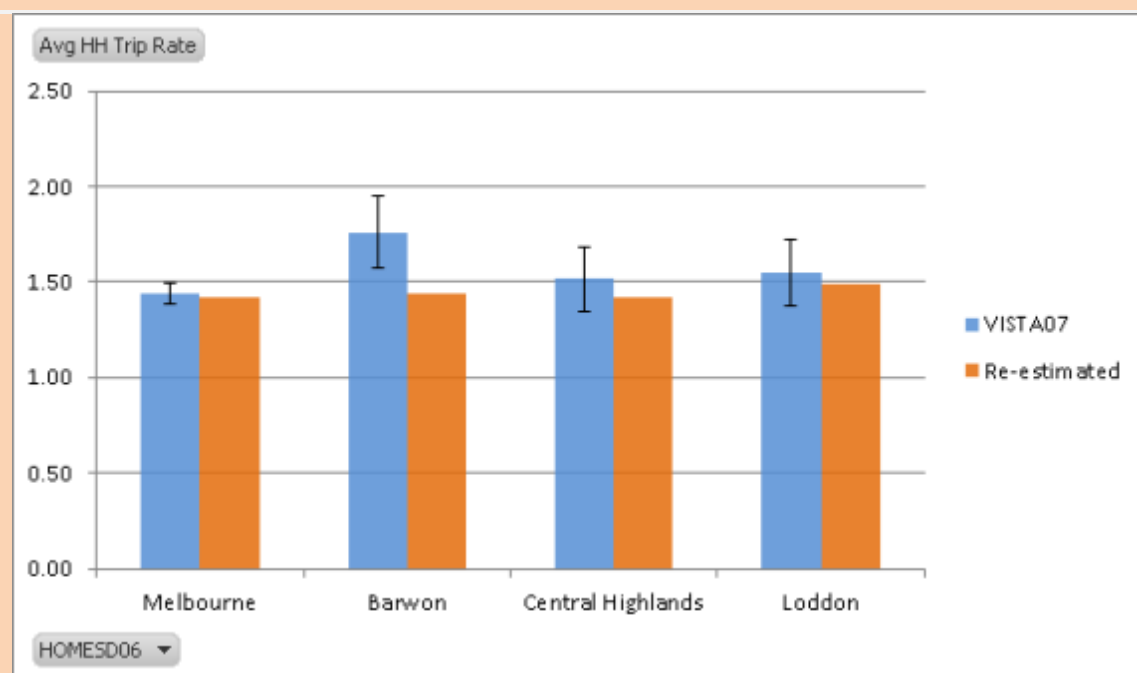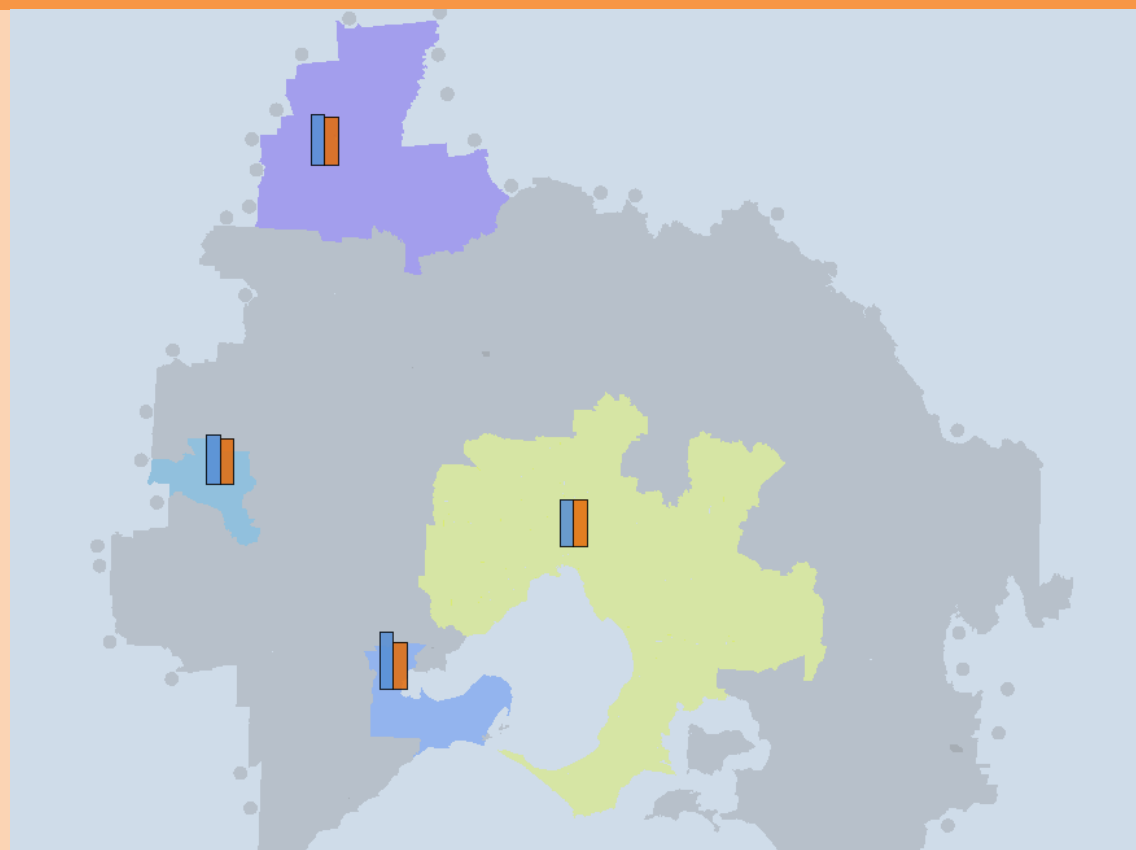
Figure 43 - Comparison of Modelled and VISTA07 Trip Rates by SD (Shopping Trips)

Avg HH Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.
Melbourne	1.44	1.43	-1%	± 4%
Barwon	1.76	1.45	-17%	±11%
Central Highlands	1.52	1.43	-6%	±11%
Loddon	1.55	1.49	-4%	±11%

Table 33 - Comparison of Modelled and VISTA07 Trip Rates by SD (Shopping Trips)

5.7 Home Based Recreation

5.7.1 Travel Market

This section provides a high level analysis of the market for *Home Based Recreation*, which we will refer to simply as recreational travel.

The breakdown of recreational trips according to the Zenith person classification is seen in Figure 44 below.
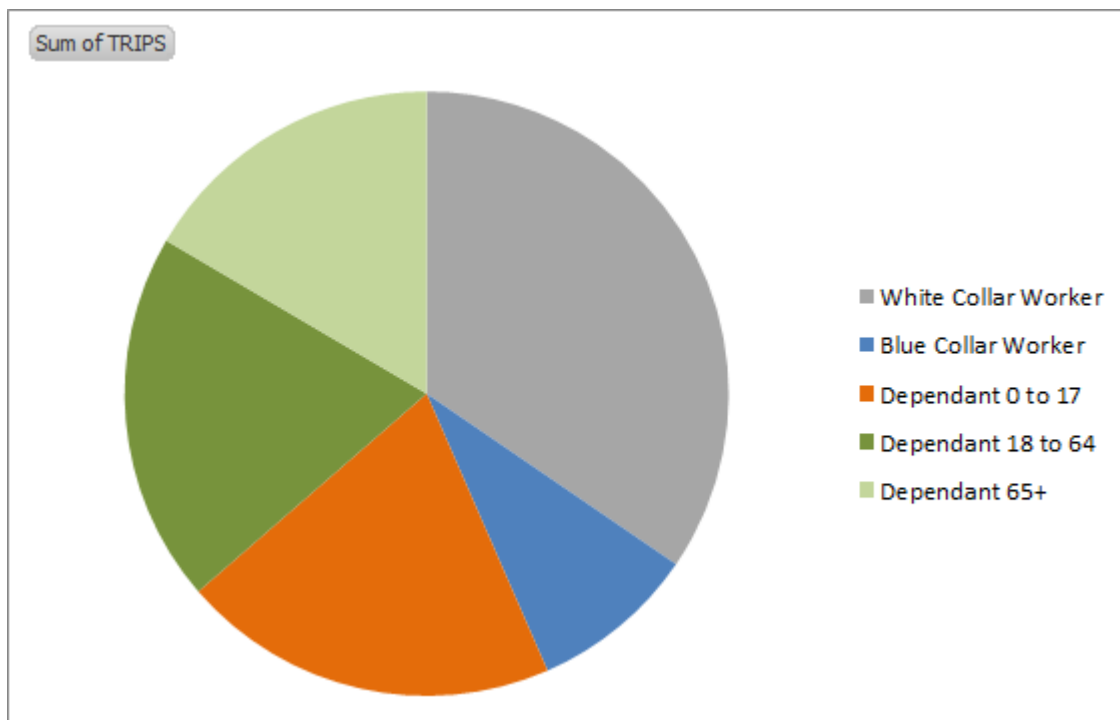
Figure 44 - The breakdown of Recreational Trips by Zenith Variables

Approximately 35% of recreational trips are made by white collar workers. Dependants aged 0 to 17 and 18 to 64 each account for 20% of trips, with dependants 65+ and blue collar workers making up the remainder with 16% and 9% respectively.

A further breakdown of the market by main activity is presented in Figure 45 below.
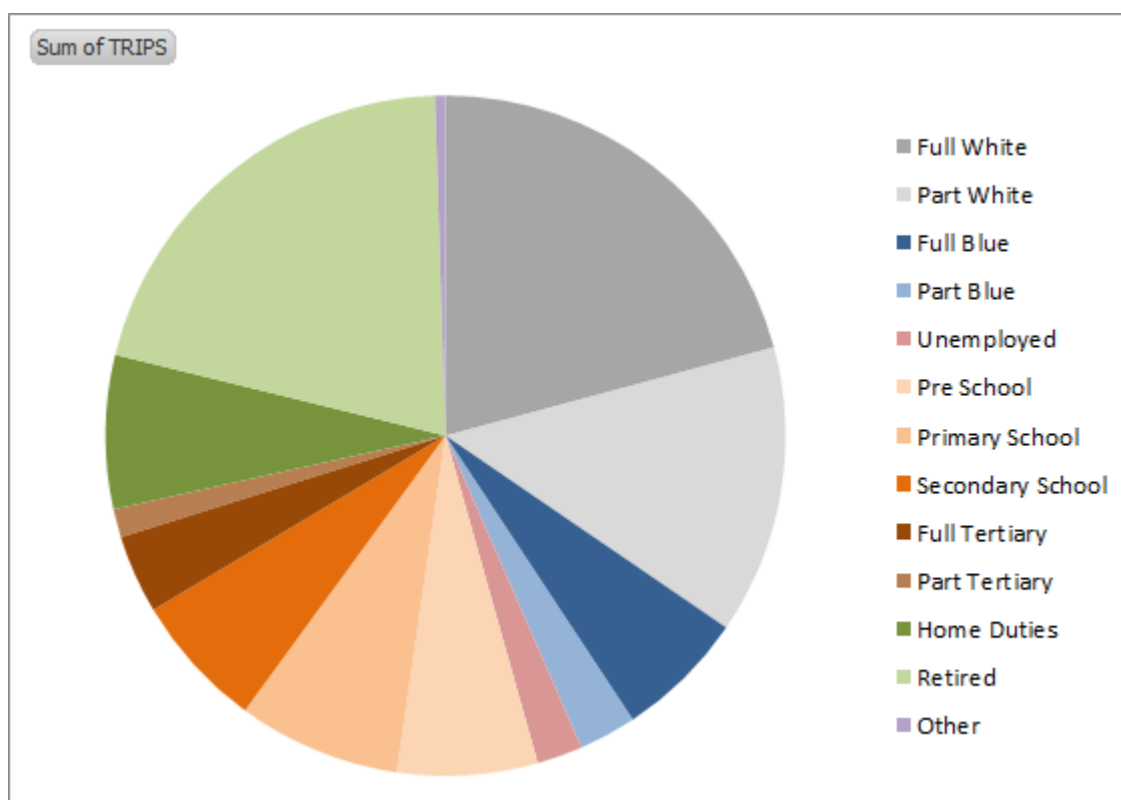
Figure 45 - The Breakdown of Recreational Trips by Main Activity

The average trip rate per person for each of the Zenith person types is shown in Figure 46 below. Dependants 65+ make recreation trips most frequently, followed by dependants 18–64. Blue collar workers make significantly less trips than all other groups, with 0.29 trips per day.
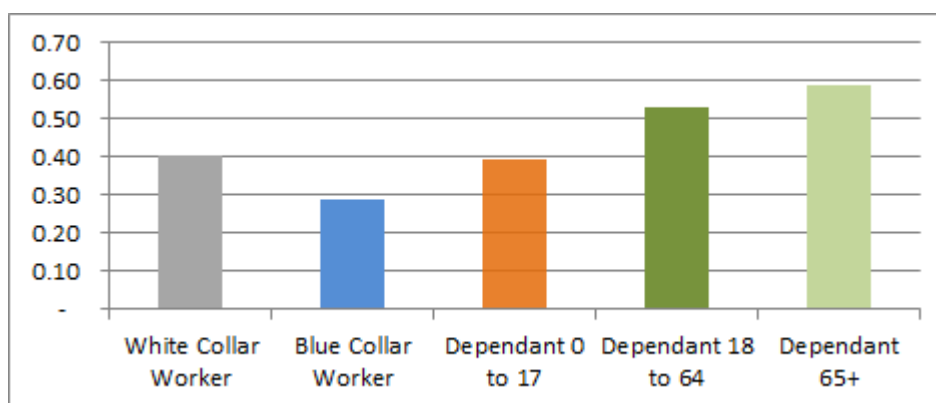
Figure 46 - Average Recreational Trip Rate per Person by Zenith Variables

A further breakdown of trip rates by main activity group is provided in Figure 47. Relative to other trip purposes, recreational trip rates are very even across main activity groups. It seems that people from all walks of life participate in recreation.

Retirees, and those engaged in home duties tend to recreate more than average, while full time workers (especially blue collar) tend to less than average. The difference between part and full time collar workers is significant.
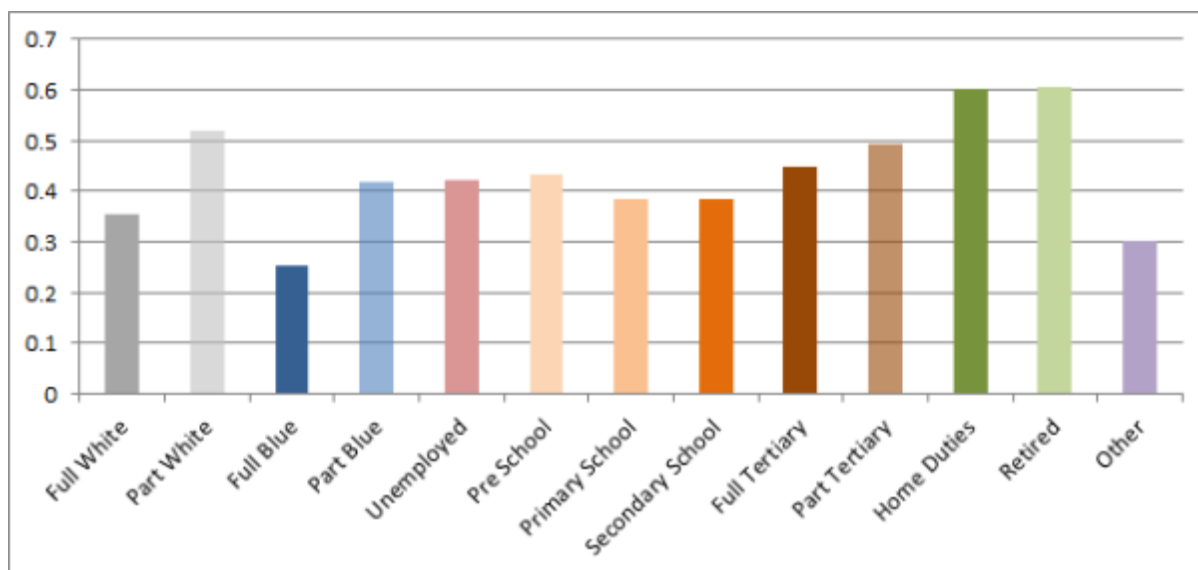
Figure 47 - Average Recreational Trip Rate by Main Activity

5.7.2   Model Estimation

5.7.2.1   Parameter Estimates

The re-estimated model parameters for home based recreation are presented in Table 34 below.

Parameter	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE	STANDARD ERROR
WHITEWORKERS_1	0.189	2.567	0.011	0.074
WHITEWORKERS_2	0.521	5.607	0.000	0.093
WHITEWORKERS_3+	1.046	5.887	0.000	0.178
DEPS_0TO17_1	0.119	1.375	0.169	0.087
DEPS_0TO17_2	0.527	6.150	0.000	0.086
DEPS_0TO17_3+	0.929	7.448	0.000	0.125
DEPS_18TO64_1	0.365	5.355	0.000	0.068
DEPS_18TO64_2	0.400	3.165	0.002	0.126
DEPS_18TO64_3+	0.898	3.257	0.002	0.276
DEPS_65PLUS_1	0.336	3.933	0.000	0.085
DEPS_65PLUS_2+	0.728	6.291	0.000	0.116
CARS_1	0.410	5.349	0.000	0.077
CARS_2	0.563	6.480	0.000	0.087
CARS_3+	0.661	5.749	0.000	0.115

Table 34 –Parameter Estimates and Properties for Recreational Travel

Consistent with their high trip rate, dependants 65+ have the largest parameters, with 0.336 and 0.728 for households with 1 and 2+ such dependants.

For the other person types, the parameters are quite consistent across person types. Notable exceptions include:

- DEPS_18TO64_1: 0.365. This parameter is comparatively large (even higher than the parameter for having 1 dependant 65+). This dependant may act as an enabler for the recreation of other household members (for example, by chauffeuring children to and from recreational activities).
- Blue collar workers: no significant (or intuitive) parameters were found for blue collar workers, meaning that they have a parameter of zero in the model. This isn't to say that they make no trips. With parameters on 1, 2 or 3+ cars, the only households for which the model will predict zero trips are households consisting purely of blue collar workers, and having zero cars.

As with shopping, the owning of at least one car plays a key enabling role in recreational travel. On average, households with no car will make 0.41 less trips than households with one car, all other things being equal.

5.7.3   Model Validation

5.7.3.1   Demographic Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of demographic aggregation.

Referring to Table 35 below, it can be observed that:

- Households with 1 and 2 people have the largest trip rate *per person,* with per person trip rates of 0.54 and 0.485 (0.97 / 2). As households increase in size beyond two, each extra person tends to add about 0.3 trips. The model is reasonably successful in replicating this pattern, despite slightly over-predicting the trip rate of single person households, and conversely under-predicting 3 and 4 person households.
- Income appears to play a key role in the propensity to make recreational travel, with trips increasing as income increases. With income variables absent from the model, it is unsurprising that the model slightly over-predicts the trip rate of low income households and under-predicts for high income households (especially households in the highest income quintile). This might be worth exploring at a later date.
- There is a strong relationship between recreational travel and car ownership. Households with no cars make less than half the recreational trips of households that own a car.

Average Household Trip Rates by Household Characteristics
Home Based Recreation | Re-estimated Zenith Model
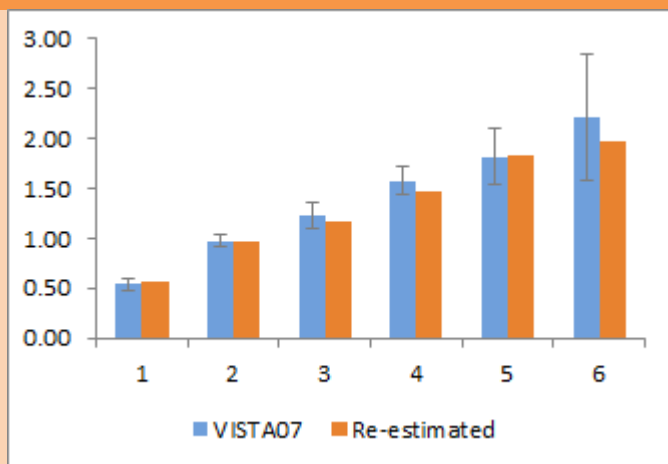
Household Size	VISTA07	Re-estimated	Diff	95% C.I.	Sample
1	0.54	0.57	7%	± 10%	1,571
2	0.97	0.98	0%	± 7%	2,682
3	1.23	1.17	-4%	± 10%	1,182
4	1.57	1.48	-6%	± 9%	1,277
5	1.81	1.84	1%	± 15%	392
6	2.21	1.96	-11%	± 29%	103

Household Size
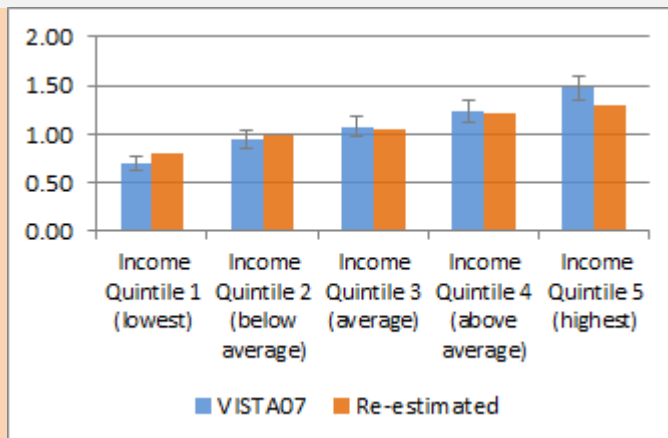
Income Quintile	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Income Quintile 1 (lowest)	0.70	0.80	14%	± 11%	1,423
Income Quintile 2 (below average)	0.95	0.98	3%	± 10%	1,409
Income Quintile 3 (average)	1.08	1.05	-2%	± 10%	1,467
Income Quintile 4 (above average)	1.23	1.21	-2%	± 9%	1,441
Income Quintile 5 (highest)	1.47	1.31	-11%	± 8%	1,488

Household Income
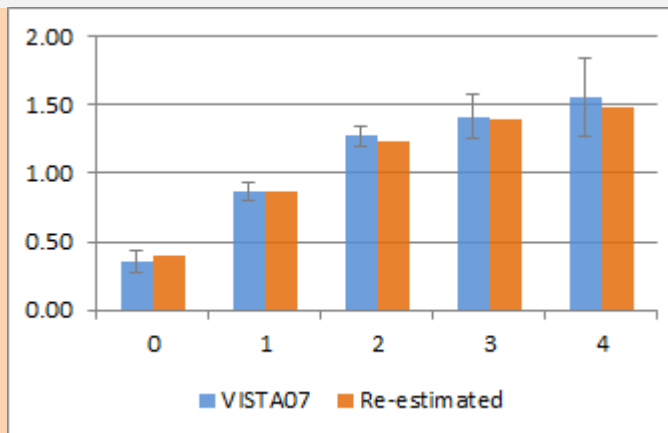
Car Ownership	VISTA07	Re-estimated	Diff	95% C.I.	Sample
0	0.36	0.40	11%	± 22%	483
1	0.87	0.87	0%	± 8%	2,614
2	1.27	1.24	-3%	± 6%	3,105
3	1.41	1.39	-1%	± 11%	745
4	1.56	1.49	-5%	± 19%	225

Cars Owned

Table 35 - Validation by Demographic Categories (Recreational Trips)

5.7.3.2   Spatial Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of demographic aggregation.

Referring to the LGA analysis (Figure 48 and Table 36), it can be observed that:

- As with shopping, the model is unable to explain any of the variation between the trip rates of the sampled LGAs. Once again, with an average sample size of only 213 households per LGA, there will be a great deal of natural random variation between LGAs due to sampling. Nonetheless, there do appear to be spatial patterns which the model is failing to predict (such as higher trip rates in the inner city).

The picture becomes clearer if we consider the Concentric Ring analysis. Referring to Figure 49 and Table 37, it can be observed that:

- In VISTA, household trip rates are highest in Geelong. In Melbourne, they are highest in the inner city, and decline as one moves toward the outer suburbs. This is an interesting effect. Given that household sizes tend to increase the further one moves from the city, the VISTA survey suggests trip rates are declining as household size increases! Clearly, there is something missing from our explanation (and indeed the model!) which will explain why households closer to the city make drastically more recreational trips. Accessibility to places of recreation may be one explanation; income may be another. This might be worth exploring at a later date.

At the SD level (Figure 50 and Table 38), another interesting pattern emerges:

- Households in Melbourne, the Central Highlands and Loddon average between 1.06 and 1.10 trips per household, while households in Barwon average nearly 1.34 (lucky them!). The Barwon SD has been a regular outlier in most trip purposes; it will be interesting to see if the pattern is repeated in VISTA09.

Average Household Trip Rate by LGA
Home Based Recreation | Re-estimated Zenith Model
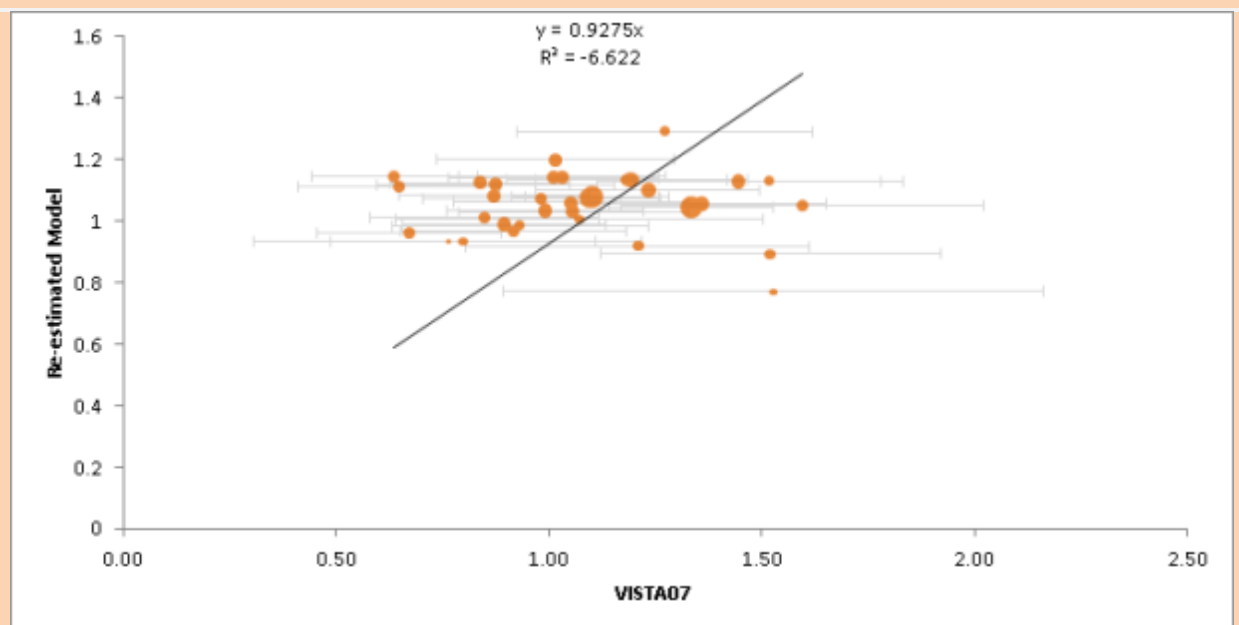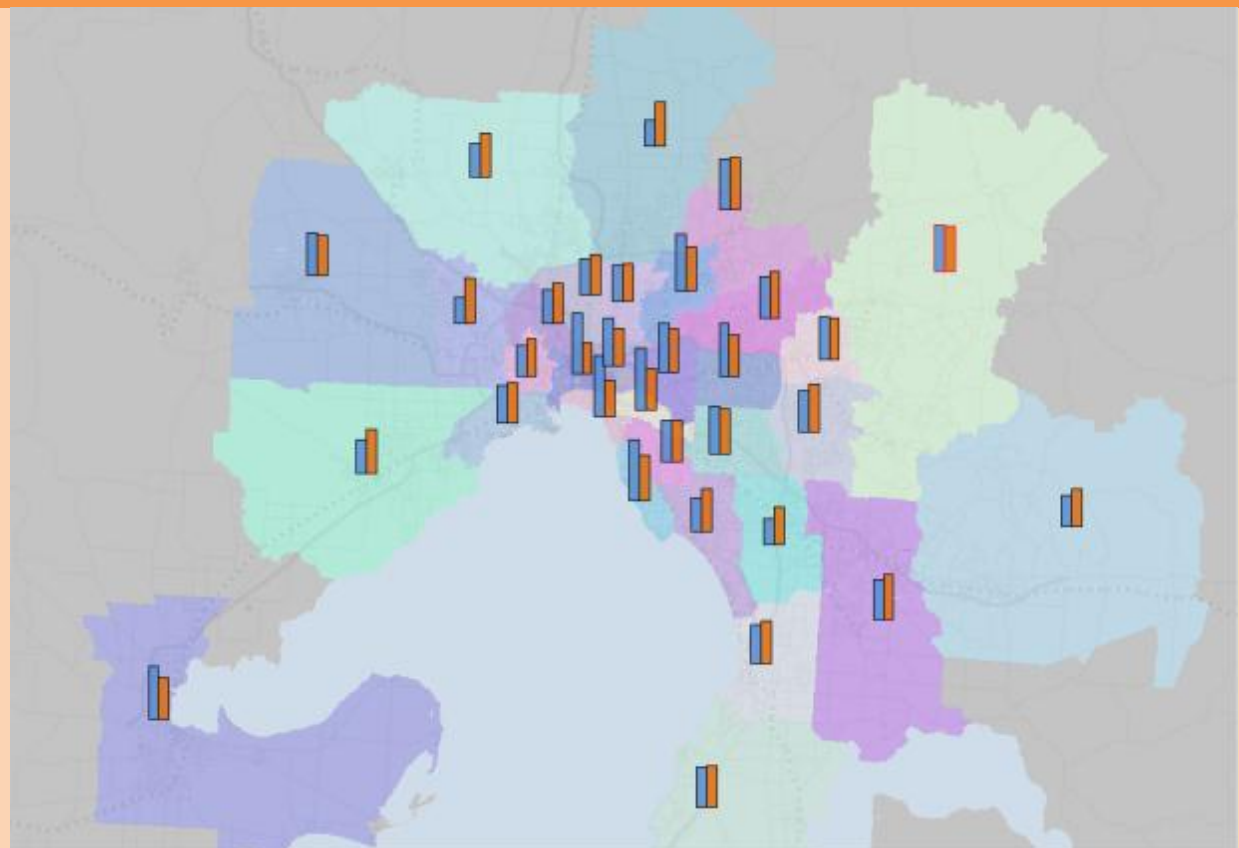
Figure 48 – Comparison of Modelled and VISTA07 Trip Rates by LGA (Recreational School Trips)

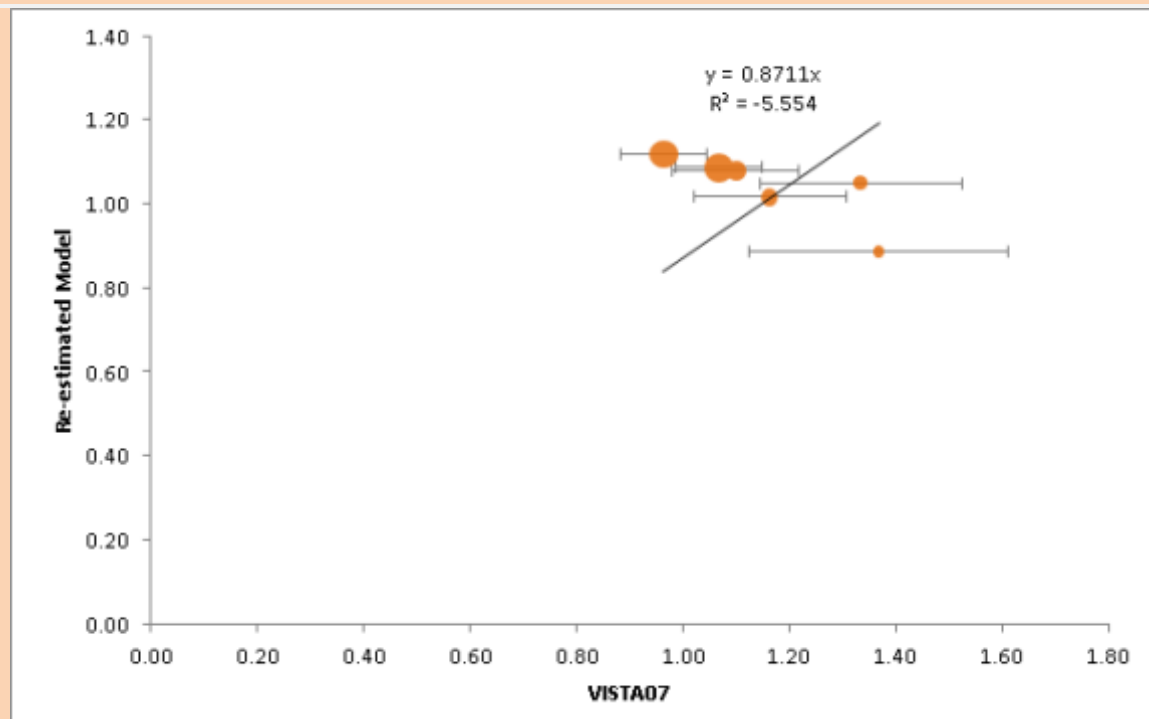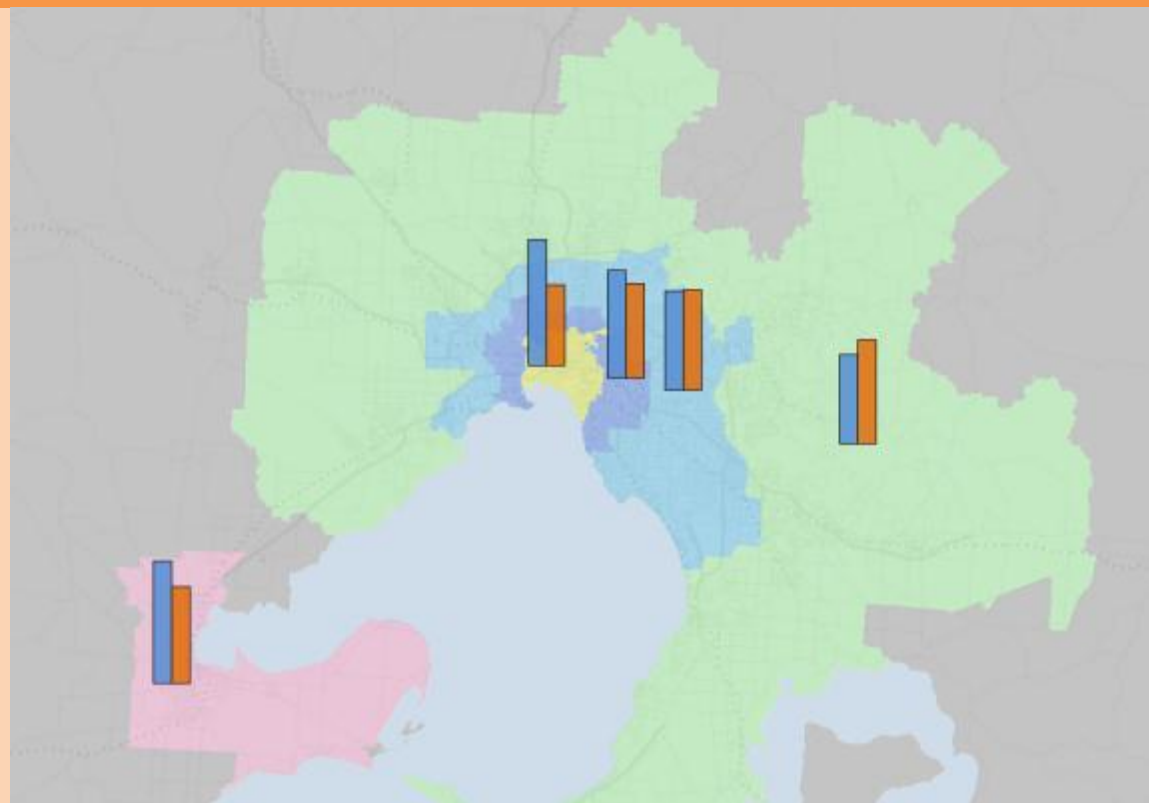| Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Ballarat (C)	1.10	1.08	-2%	±14%	581
Banyule (C)	1.45	1.13	-22%	±23%	240
Bayside (C)	1.52	1.13	-25%	±21%	153
Boroondara (C)	1.23	1.10	-11%	±21%	265
Brimbank (C)	0.64	1.15	80%	±31%	171
Cardinia (S)	0.76	0.93	22%	±60%	32
Casey (C)	1.01	1.14	13%	±25%	220
Darebin (C)	0.92	0.97	5%	±29%	194
Frankston (C)	0.98	1.07	9%	±28%	181
Glen Eira (C)	1.05	1.06	1%	±26%	197
Greater Bendigo (C)	1.10	1.08	-2%	±17%	488
Greater Dandenong (C)	0.67	0.96	43%	±32%	167
Greater Geelong (C)	1.34	1.05	-22%	±14%	572
Hobsons Bay (C)	0.93	0.99	6%	±32%	128
Hume (C)	0.84	1.12	34%	±25%	189
Kingston (C)	0.87	1.08	24%	±26%	225
Knox (C)	1.01	1.20	18%	±27%	223
Manningham (C)	1.03	1.14	11%	±24%	242
Maribyrnong (C)	0.80	0.93	17%	±39%	104
Maroondah (C)	1.06	1.03	-2%	±26%	225
Melbourne (C)	1.53	0.77	-50%	±41%	62
Melton (S)	1.07	1.00	-6%	±40%	88
Monash (C)	1.19	1.13	-5%	±19%	326
Moonee Valley (C)	0.85	1.01	19%	±32%	153
Moreland (C)	0.89	0.99	11%	±27%	239
Mornington Peninsula (S)	0.99	1.03	4%	±23%	251
Nillumbik (S)	1.27	1.29	1%	±27%	112
Port Phillip (C)	1.52	0.89	-41%	±26%	129
Stonnington (C)	1.60	1.05	-34%	±27%	146
Whitehorse (C)	1.36	1.06	-22%	±21%	239
Whittlesea (C)	0.65	1.11	71%	±37%	173
Wyndham (C)	0.87	1.12	28%	±32%	179
Yarra (C)	1.21	0.92	-24%	±33%	146
Yarra Ranges (S)	1.19	1.13	-4%	±24%	188

Table 36 - Comparison of Modelled and VISTA07 Trip Rates by LGA (Recreational Trips)

Average Household Trip Rate by Region
Home Based Recreation | Re-estimated Zenith Model

Figure 49 - Comparison of Modelled and VISTA07 Trip Rates by Region (Recreational Trips)

Avg Household Trip Rate	VISTA07	Re-estimated	Diff	95% CI	Sample
Inner City	1.37	0.89	-35%	± 18%	377
Inner Suburbs	1.16	1.02	-13%	± 12%	813
Middle Suburbs	1.07	1.09	2%	± 8%	2,328
Outer Suburbs	0.96	1.12	16%	± 8%	2,069
Major Regional Centre	1.34	1.05	-21%	± 14%	572
Regional	1.10	1.08	-2%	± 11%	1,069

Table 37 - Comparison of Modelled and VISTA07 Trip Rates by Region (Recreational Trips)

Average Household Trip Rate by SD
Home Based Recreation | Re-estimated Zenith Model
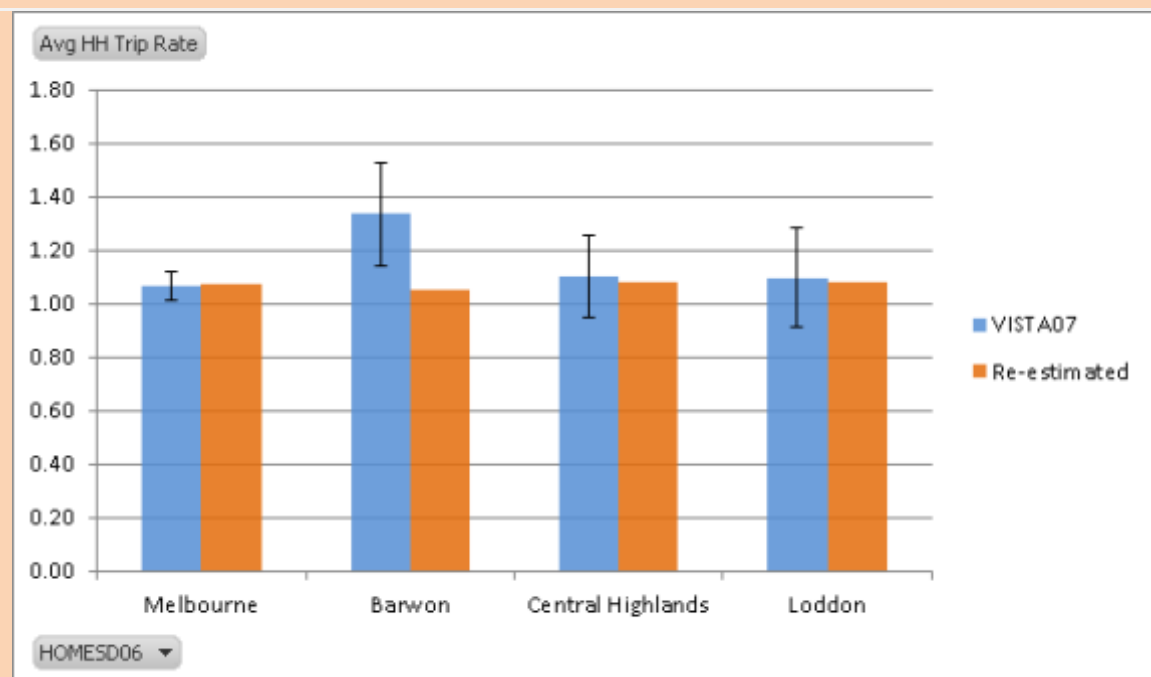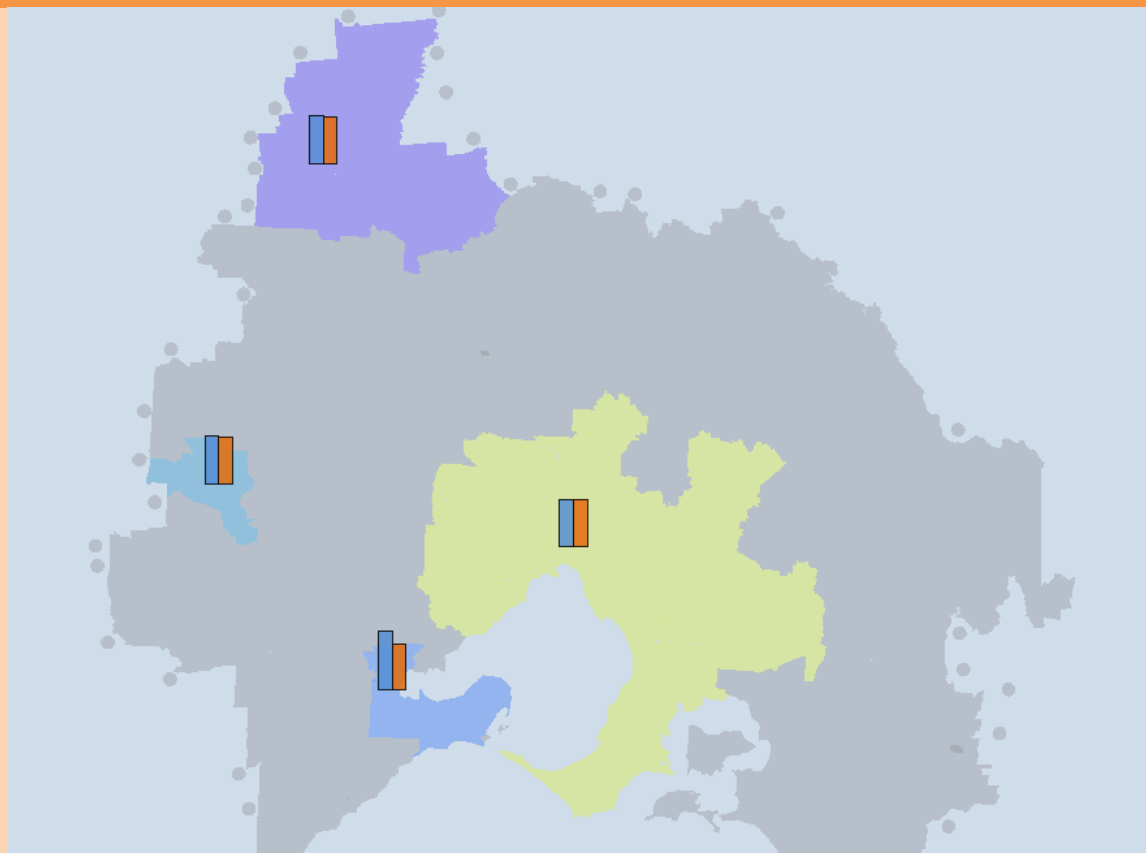
Figure 50 - Comparison of Modelled and VISTA07 Trip Rates by SD (Recreational Trips)

Avg HH Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.
Melbourne	1.06	1.07	1%	±5%
Barwon	1.34	1.05	-22%	±14%
Central Highlands	1.10	1.08	-2%	±14%
Loddon	1.10	1.08	-2%	±17%

Table 38 - Comparison of Modelled and VISTA07 Trip Rates by SD (Recreational Trips)

5.8 Home Based Other

5.8.1 Travel Market

This section provides a high level analysis of the market for *Home Based Other,* which we will refer to simply as other travel. The key sub-purposes included in Home Based Other are:

- Serving the needs of a passenger (picking up / dropping off)
- Accompanying someone (eg. a small child accompanying their parent)

The breakdown of other trips according to the Zenith person classification is seen in Figure 51 below.
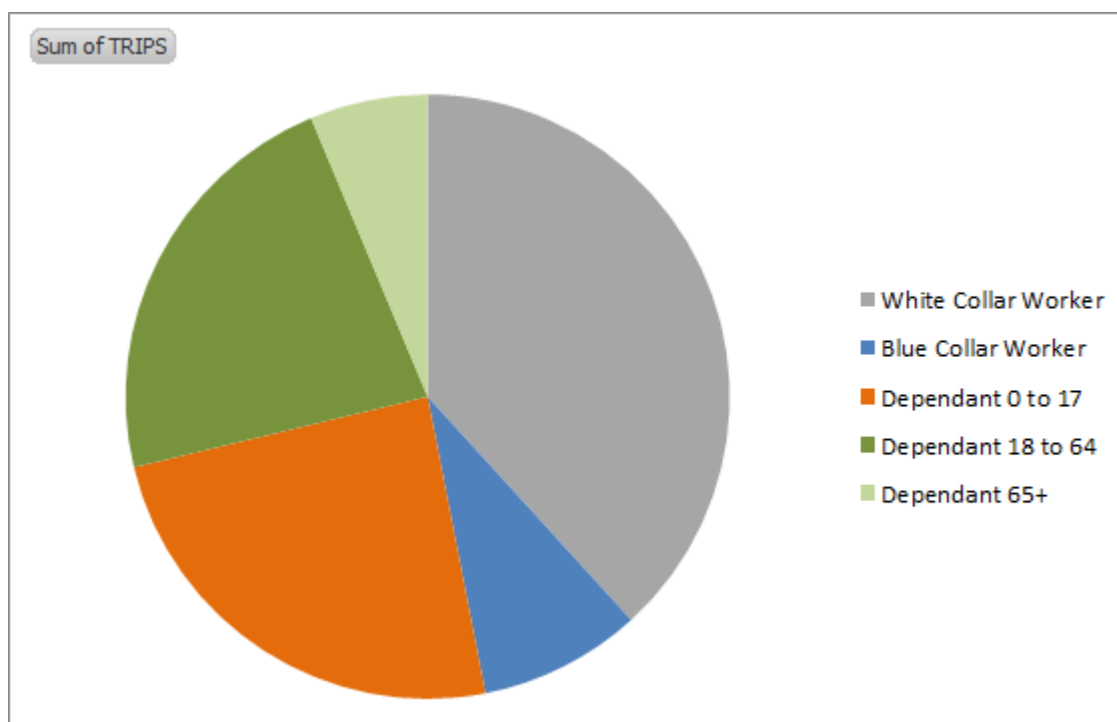
Figure 51 - The breakdown of Other Trips by Zenith Variables

Approximately 38% of these trips are made by white collar workers, 24% by dependants 0-17, 22% by dependants aged 18 to 64, 9% by blue collar workers, and 6% by dependants aged 65 or greater.

The breakdown of trips by main activity group (Figure 52) reveals that part time white collar workers play an important role, presumably through the chauffeuring of other household members. It is also noteworthy that nearly 16% of other trips are made by pre-school children (ie. children not yet at school).
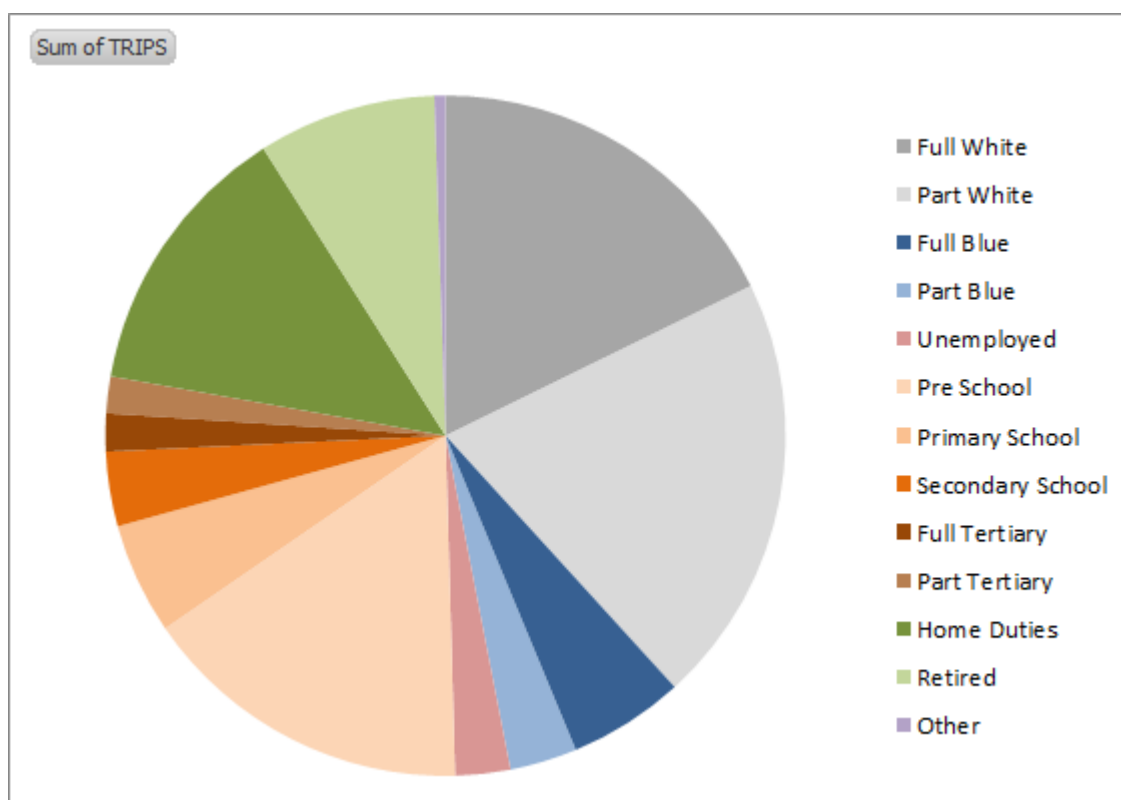
Figure 52 - The Breakdown of Other Trips by Main Activity

The average trip rate per person for each of the Zenith person types is shown in Figure 53 below. On average, dependants aged 18 to 64 are the most frequent makers of other trips, averaging 0.87 other trips per day. Dependants 65+ are least likely to undertake other travel.
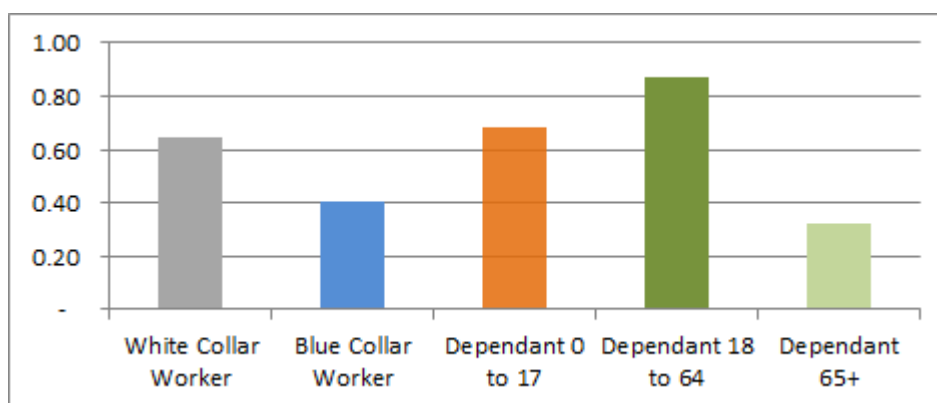
Figure 53 - Average Other Trip Rate per Person by Zenith Variables

The picture of trip rates is clearer when split by main activity groups, as illustrated in Figure 54 below. Children not yet at school, and those engaged in home duties are by far the most likely to undertake other trips, with each averaging around 1.5 trips per day. Primary and secondary school children are least likely.

It is interesting to note the drastic difference between part and full time workers. In particular, part time white collar workers are heavily engaged in other travel.
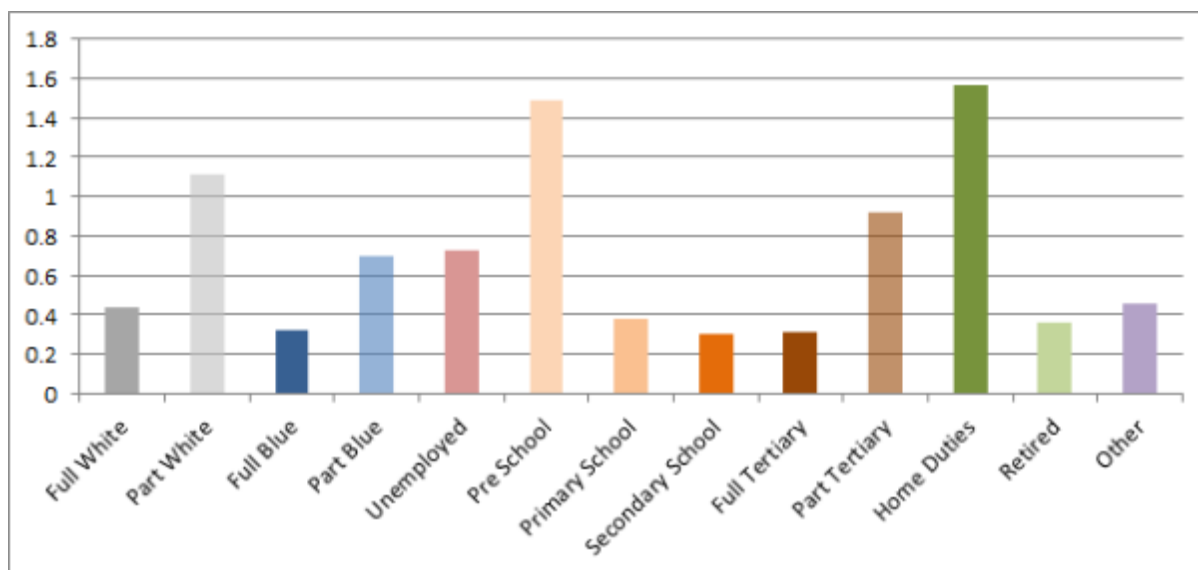
Figure 54 - Average Other Trip Rate by Main Activity

5.8.2   Model Estimation

5.8.2.1   Parameter Estimates

The re-estimated model parameters for home based other are presented in Table 39 below.

Parameter	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE	STANDARD ERROR
WHITEWORKERS_1	0.100	1.132	0.258	0.088
WHITEWORKERS_2+	0.164	1.509	0.132	0.109
DEPS_0TO17_1	1.753	17.813	0.000	0.098
DEPS_0TO17_2	3.725	38.431	0.000	0.097
DEPS_0TO17_3+	6.100	43.201	0.000	0.141
DEPS_18TO64_1+	0.500	6.560	0.000	0.076
DEPS_65PLUS_1	0.235	2.189	0.030	0.107
DEPS_65PLUS_2+	0.417	3.042	0.003	0.137
CARS_1	0.495	3.627	0.000	0.137
CARS_2	0.581	4.111	0.000	0.141
CARS_3+	0.724	4.536	0.000	0.160
constant	-0.317	-2.212	0.028	0.143

Table 39 –Parameter Estimates and Properties for Other Travel

By far and away the biggest factor in the number of home based other trips is the number of children in the household. Parameters of 1.75, 3.73 and 6.10 are estimated for households with 1, 2 and 3+ dependants aged 0-17. It appears that the number of trips is fairly linear with the number of 0-17's, with an average rate of about 1.8 trips per dependent child.

The presence of an adult dependant also has a significantly positive effect on other trips, with a parameter of 0.5 for any household that has at least one dependant aged 18-64. An adult dependant will generally act as the chauffeur.

The number of cars owned by the household also plays a key role in trip making. For the types of trips represented by this trip purpose (chauffeuring, accompanying someone), a car is close to essential. This is illustrated by the parameter of 0.495 for households with one car, as compared with an implied parameter of zero for households who don't own a car.

5.8.3   Model Validation

5.8.3.1   Demographic Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of demographic aggregation.

Referring to Table 40 below, it can be observed that:

- Home based other trip rates increase as household size increases, with very few trips made by 1 and 2 person households. The model generally replicates this pattern, though it does slightly under-predict the trip rate of 5 and 6 person households.
- Trip rates also increase with household income. The model is generally successful at predicting the trip rates for each of the income quintiles.
- Trip rates increase up as car ownership increases up to two cars per household. Beyond two cars, the trip rate declines slightly. This is consistent with families with children (and two cars) being the main producers of other trips. If households own more than two cars, it generally means that the children are of driving age, removing the need for a parent chauffeur. Again, the model is very successful in replicating this pattern.

Average Household Trip Rates by Household Characteristics
Home Based Education – Secondary | Re-estimated Zenith Model
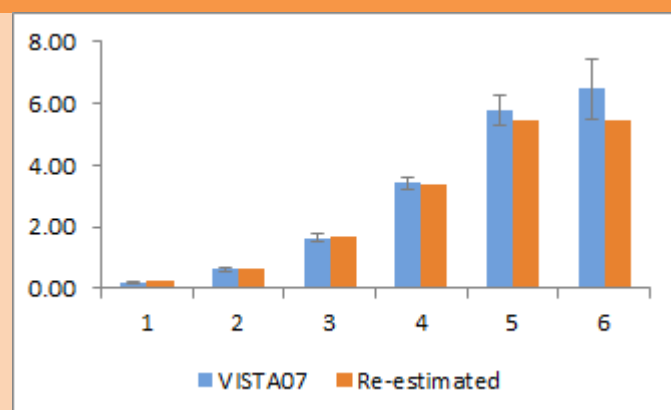
Household Size

Household Size	VISTA07	Re-estimated	Diff	95% C.I.	Sample
1	0.19	0.27	39%	± 18%	1,571
2	0.62	0.63	1%	± 8%	2,682
3	1.64	1.68	3%	± 8%	1,182
4	3.43	3.39	-1%	± 5%	1,277
5	5.78	5.46	-5%	± 8%	392
6	6.47	5.47	-15%	± 15%	103

Household Income
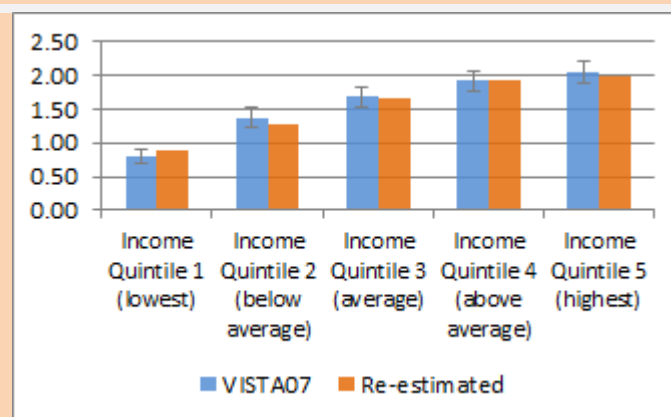
Income Quintile	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Income Quintile 1 (lowest)	0.79	0.88	11%	± 13%	1,423
Income Quintile 2 (below average)	1.36	1.29	-6%	± 11%	1,409
Income Quintile 3 (average)	1.69	1.67	-1%	± 9%	1,467
Income Quintile 4 (above average)	1.92	1.94	1%	± 8%	1,441
Income Quintile 5 (highest)	2.05	1.98	-3%	± 8%	1,488
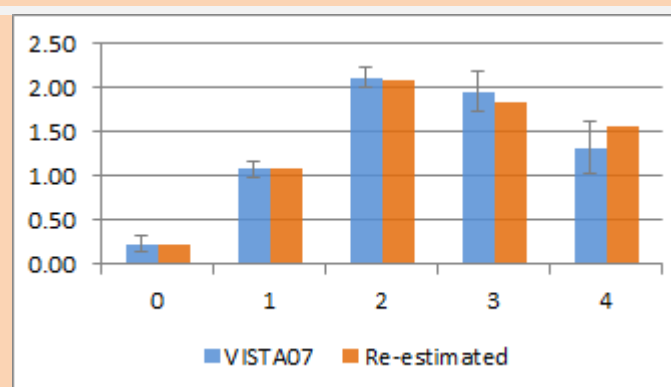
Cars Owned

Car Ownership	VISTA07	Re-estimated	Diff	95% C.I.	Sample
0	0.23	0.24	2%	± 41%	483
1	1.09	1.08	0%	± 8%	2,614
2	2.11	2.10	-1%	± 5%	3,105
3	1.96	1.83	-7%	± 11%	745
4	1.32	1.56	18%	± 22%	225

Table 40 - Validation by Demographic Categories (Other Trips)

5.8.3.2   Spatial Validation

The re-estimated model has been applied to the responding households in VISTA07, with predicted and actual trips compared at various levels of spatial aggregation.

Referring to the LGA analysis (Figure 55 and Table 41), it can be observed that:

- Home based other trip rates are generally higher as one moves away from the central business district.
- The model is quite successful in explaining the variation between the LGA trip rates, with an R-Squared of 0.72.

The relationship between trip making and the distance from the CBD is clearer in the Concentric Rings analysis (Figure 56 and Table 42), which indicates that trip rates increase from 0.96 trips per household in the Inner City to 1.74 trips per household in the outer suburbs. The modelled is able to replicate this pattern.

Finally, at the SD level (Figure 57 and Table 43), the model accurately predicts trip rates for Melbourne and Loddon, slightly under-predicts in Barwon, and slightly over-predicts in the Central Highlands. These differences may, however, be due to sampling error, with the predictions lying well within a 95% interval for the true mean.

Average Household Trip Rate by LGA
Home Based Other | Re-estimated Zenith Model
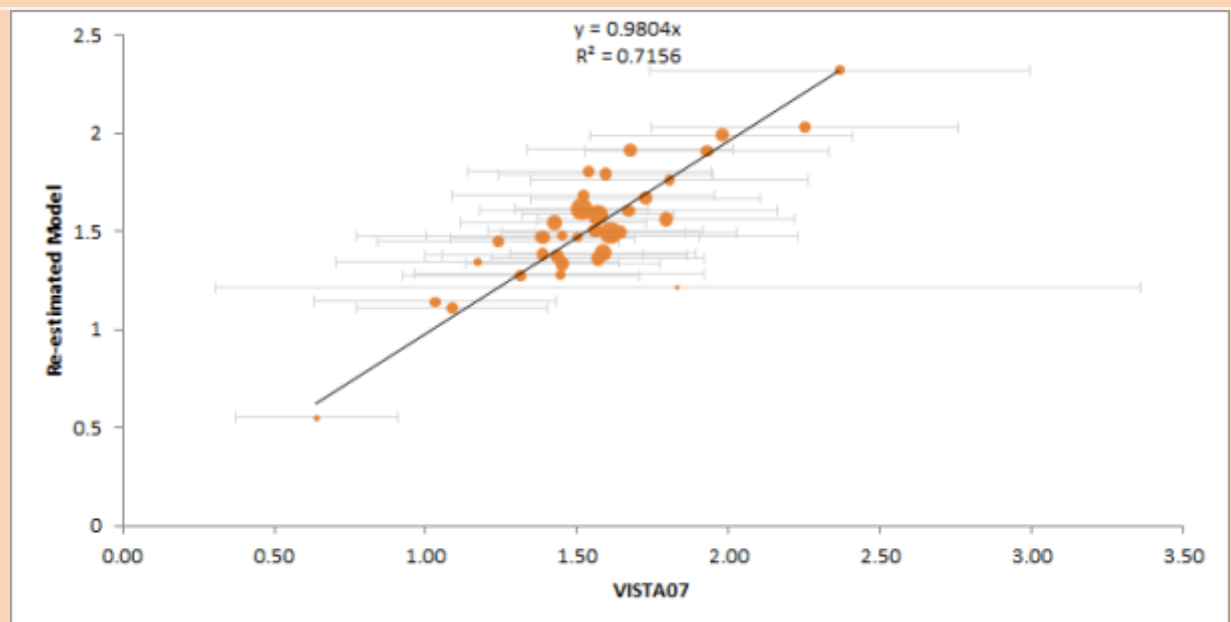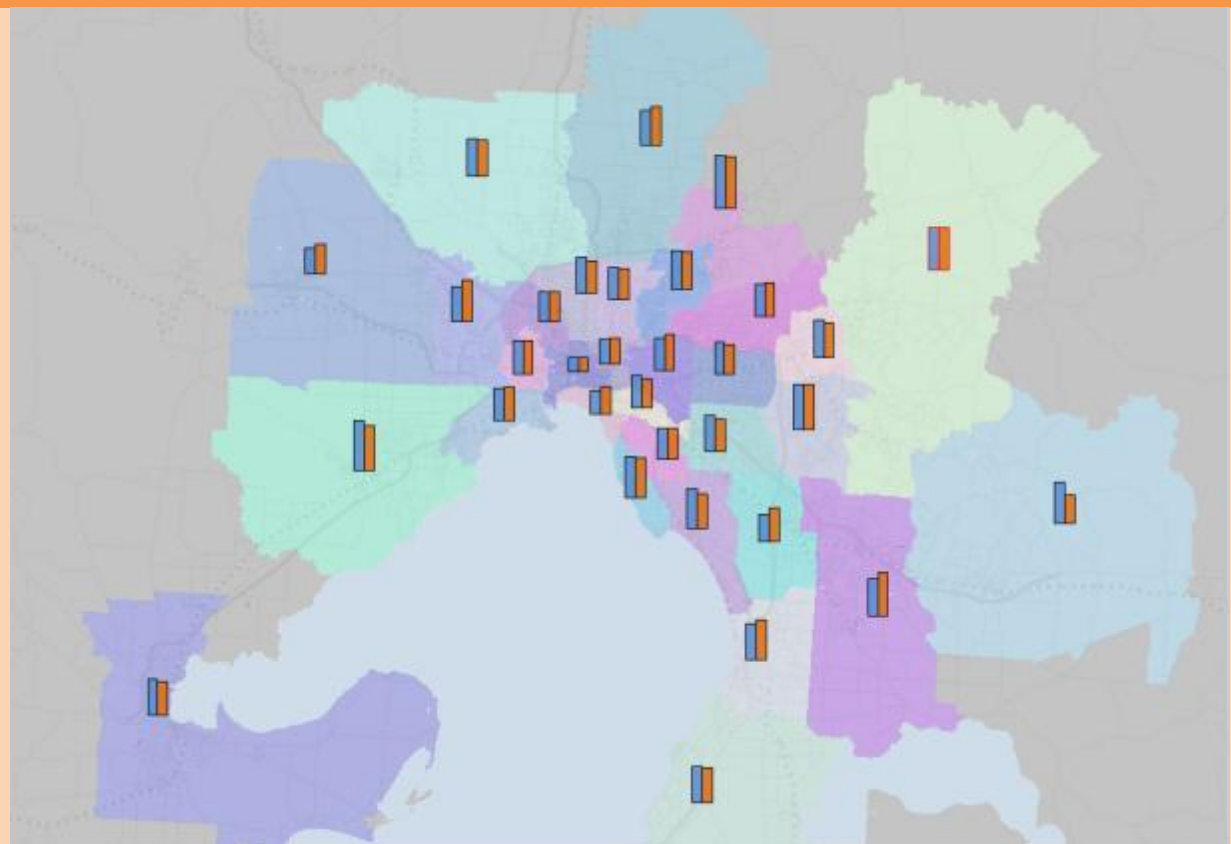
Figure 55 – Comparison of Modelled and VISTA07 Trip Rates by LGA (Other Trips)

Avg Household Trip Rate					
	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Ballarat (C)	1.51	1.61	7%	± 14%	581
Banyule (C)	1.72	1.67	-3%	± 22%	240
Bayside (C)	1.80	1.76	-2%	± 25%	153
Boroondara (C)	1.42	1.55	9%	± 21%	265
Brimbank (C)	1.54	1.80	17%	± 26%	171
Cardinia (S)	1.83	1.21	-34%	± 83%	32
Casey (C)	1.67	1.92	15%	± 20%	220
Darebin (C)	1.43	1.38	-4%	± 30%	194
Frankston (C)	1.59	1.79	13%	± 22%	181
Glen Eira (C)	1.39	1.38	0%	± 24%	197
Greater Bendigo (C)	1.57	1.59	1%	± 16%	488
Greater Dandenong (C)	1.24	1.45	17%	± 32%	167
Greater Geelong (C)	1.61	1.50	-7%	± 15%	572
Hobsons Bay (C)	1.45	1.48	2%	± 31%	128
Hume (C)	1.67	1.61	-4%	± 29%	189
Kingston (C)	1.79	1.56	-13%	± 24%	225
Knox (C)	1.98	1.99	1%	± 22%	223
Manningham (C)	1.38	1.47	6%	± 22%	242
Maribyrnong (C)	1.50	1.47	-2%	± 48%	104
Maroondah (C)	1.64	1.50	-9%	± 24%	225
Melbourne (C)	0.64	0.55	-14%	± 42%	62
Melton (S)	1.17	1.34	15%	± 40%	88
Monash (C)	1.59	1.39	-12%	± 19%	326
Moonee Valley (C)	1.31	1.28	-3%	± 30%	153
Moreland (C)	1.57	1.36	-13%	± 22%	239
Mornington Peninsula (S)	1.56	1.51	-3%	± 23%	251
Nillumbik (S)	2.37	2.32	-2%	± 26%	112
Port Phillip (C)	1.03	1.14	11%	± 39%	129
Stonnington (C)	1.44	1.28	-11%	± 33%	146
Whitehorse (C)	1.45	1.34	-8%	± 22%	239
Whittlesea (C)	1.52	1.69	11%	± 28%	173
Wyndham (C)	2.25	2.03	-10%	± 23%	179
Yarra (C)	1.09	1.11	2%	± 29%	146
Yarra Ranges (S)	1.93	1.91	-1%	± 21%	188

Table 41 - Comparison of Modelled and VISTA07 Trip Rates by LGA (Other Trips)

Average Household Trip Rate by Region
Home Based Other | Re-estimated Zenith Model

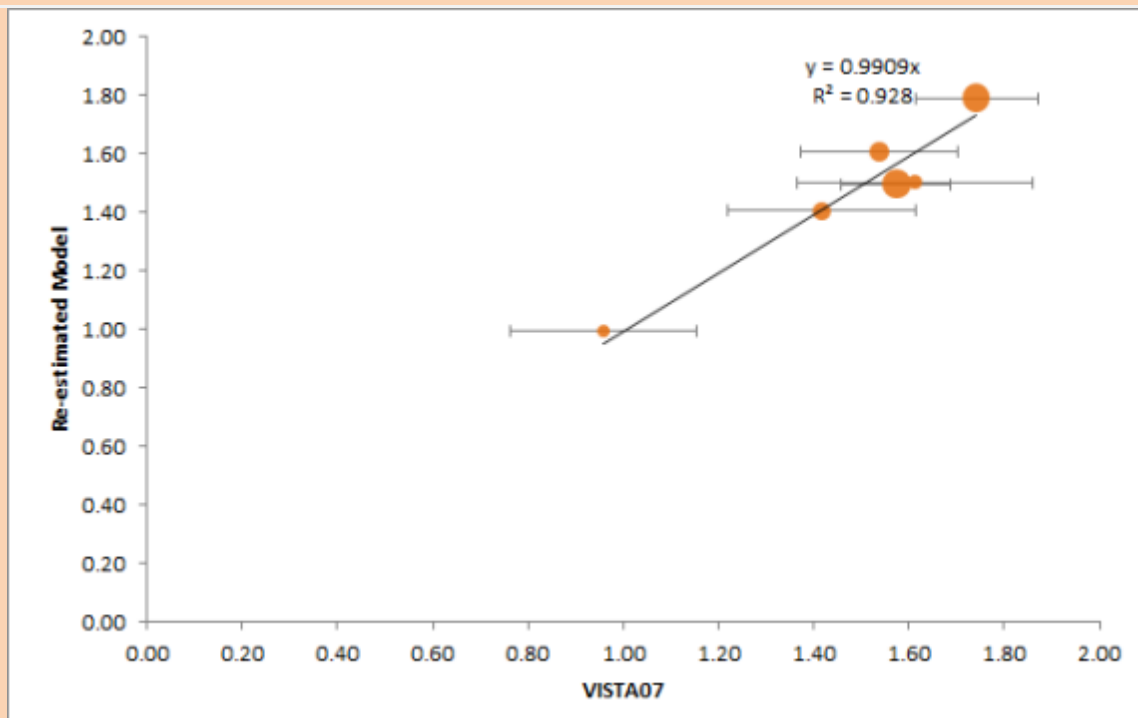*Figure 56 - Comparison of Modelled and VISTA07 Trip Rates by Region (Other Trips)*
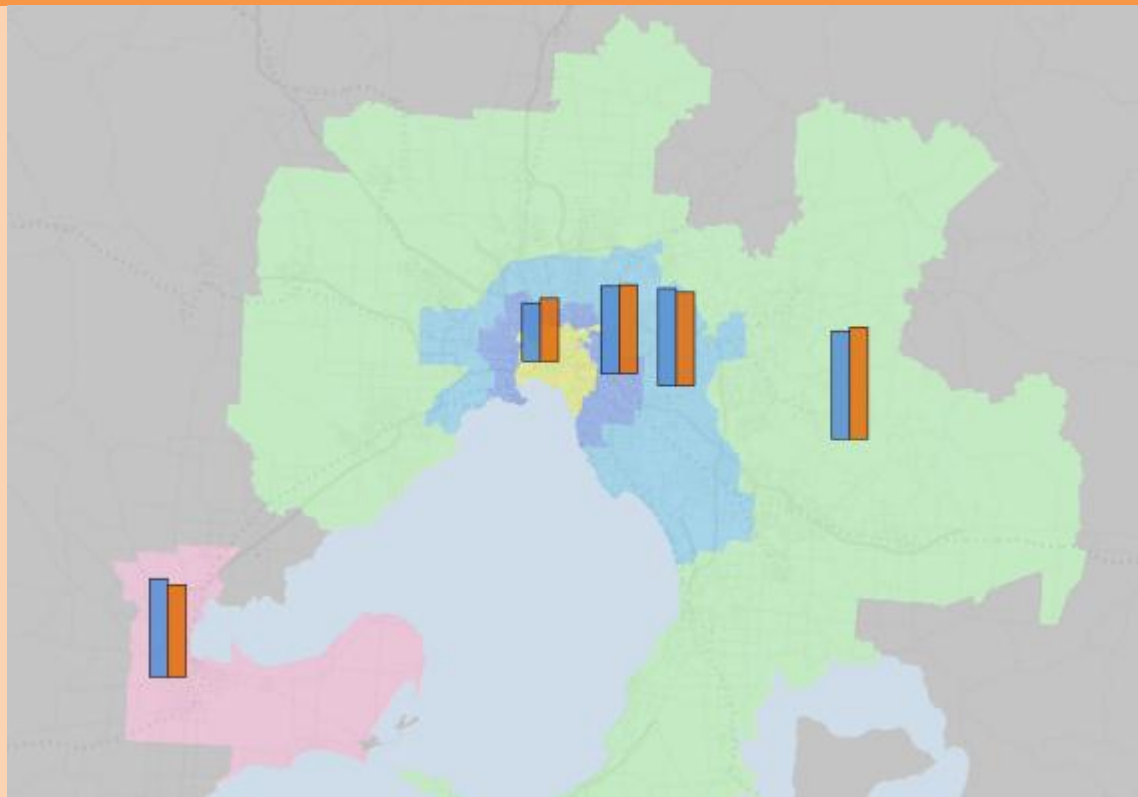
Avg Household Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Inner City	0.96	0.99	3%	± 20%	377
Inner Suburbs	1.42	1.40	-1%	± 14%	813
Middle Suburbs	1.57	1.49	-5%	± 7%	2,328
Outer Suburbs	1.74	1.79	3%	± 7%	2,069
Major Regional Centre	1.61	1.50	-7%	± 15%	572
Regional	1.54	1.60	4%	± 11%	1,069

Table 42 - Comparison of Modelled and VISTA07 Trip Rates by Region (Other Trips)

Average Household Trip Rate by SD
Home Based Other | Re-estimated Zenith Model
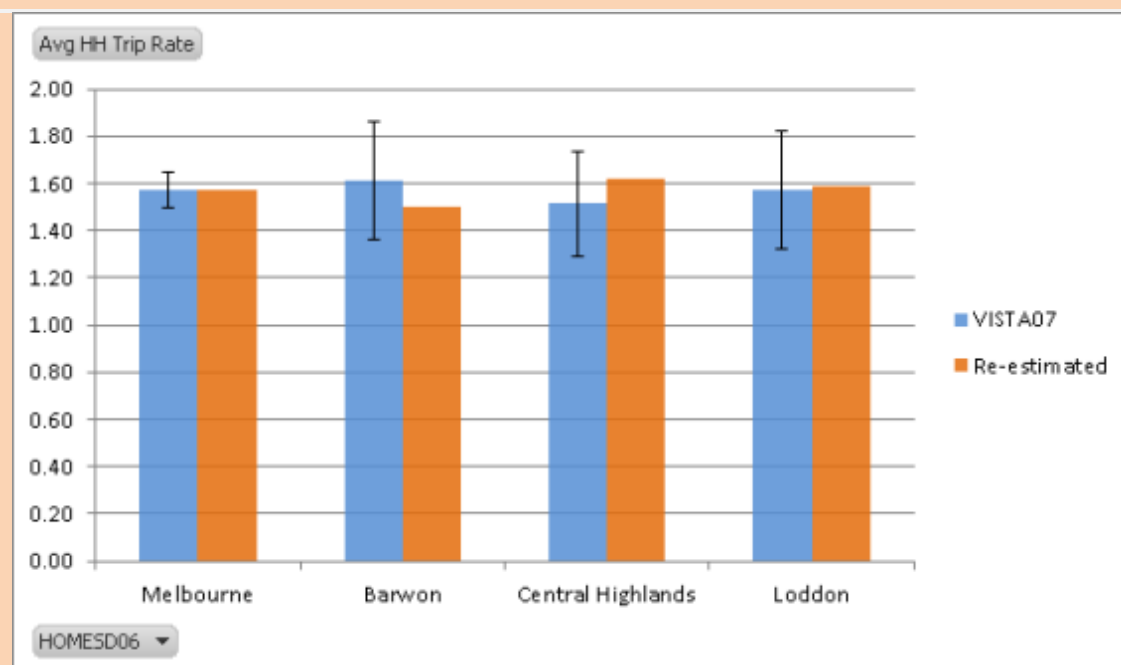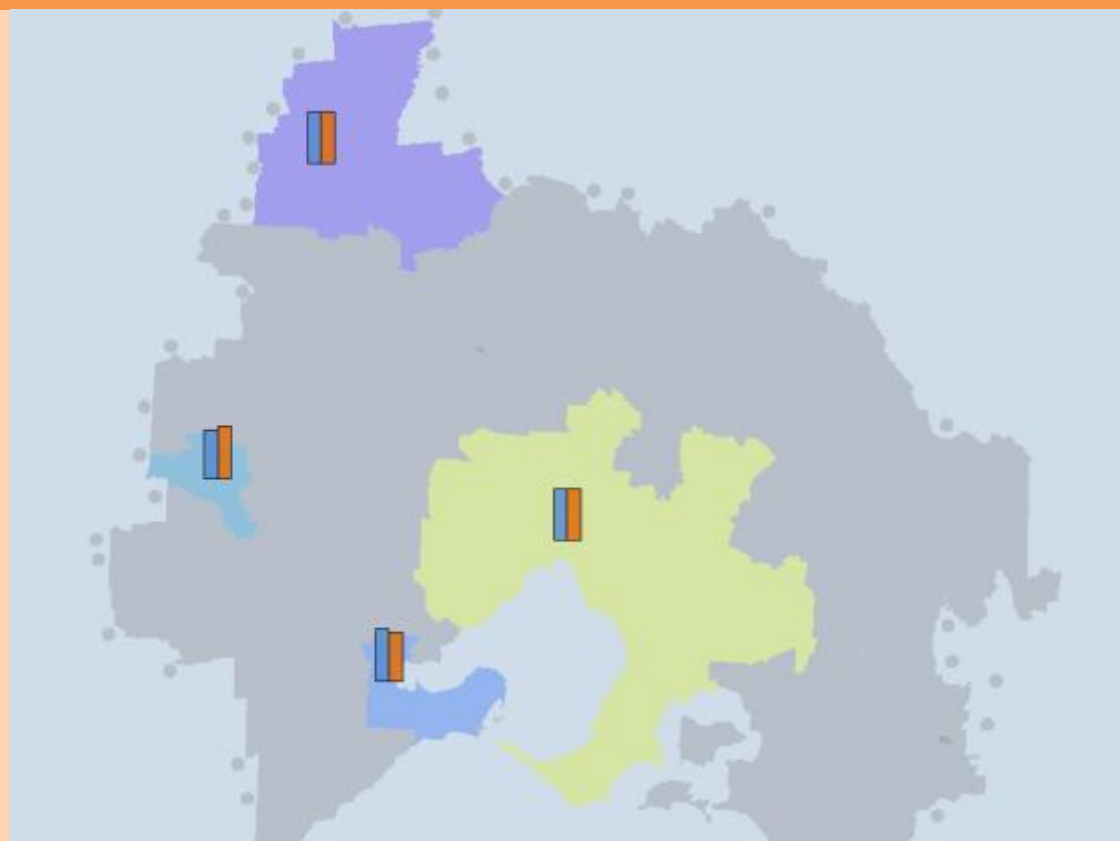
Figure 57 - Comparison of Modelled and VISTA07 Trip Rates by SD (Other Trips)

Avg HH Trip Rate	VISTA07	Re-estimated	Diff	95% C.I.	Sample
Melbourne	1.57	1.55	-1%	± 5%	5587
Barwon	1.61	1.50	-7%	± 15%	572
Central Highlands	1.51	1.61	7%	± 14%	581
Loddon	1.57	1.59	1%	± 16%	488

Table 43 - Comparison of Modelled and VISTA07 Trip Rates by SD (Other Trips)

6 Correction Factors for Under–Reporting in VISTA

VLC has compared the amount of travel reported in VISTA with other observed sources of travel data, including:

- Screenline Traffic Counts
- 2009 Rail OD survey
- 2008 Tram OD survey
- Bus ticket validations

Based on these comparisons, it appears that VISTA07 under–reports travel, especially in the Off Peak. This work is presented in *Working Paper 2 – Analysis of VISTA.*

Based on this work, correction factors have been estimated, by Trip Purpose. These factors scale up the model parameters reported in Section 5.

The correction factors are:

Trip Purpose	Inter Peak (9am - 3pm)	Evening Peak (6pm - midnight)
HBW (white)	1.35	1.00
HBW (blue)	1.75	1.00
HBE (tertiary)	2.00	1.00
HBS	1.05	1.75
HBR	1.15	1.50
HBO	1.30	1.50
WBW	1.10	1.00
WBS	2.10	1.80
WBO	3.00	1.00
SBS	1.30	2.00
SBO	1.50	1.50
ONHB	1.40	1.00

Table 44 - Under-Reporting Correction Factors

Appendix A – Definition of School and Public Holidays

The aim of defining school and public holidays is to be able to remove such dates from the VISTA07 sample, resulting in the remaining surveys representing a typical or "heavy" weekday. Key public holidays and school holiday periods were compiled for the VISTA07 survey period between 23rd April 2007 to 15th June 2008 and are described below.

Public Holidays

A list of public holidays in Victoria for the survey period was compiled and are summarised in the Table below. Public holidays for regional areas were not considered, and holidays for the metropolitan area were applied to the entire VISTA07 sample.

Victorian public holidays As set by the Public Holidays Act 1993.

Holiday	2007	2008	2009
New Year's Day	Mon 1 January	Tue 1 January	Thu 1 January
Australia Day	Fri 26 January	Mon 28 January *in lieu of Sat 26th	Mon 26 January
Labour Day	Mon 12 March	Mon 10 March	Mon 9 March
Good Friday	Fri 6 April	Fri 21 March	Fri 10 April
Easter Saturday	Sat 7 April	Sat 22 March	Sat 11 April
Easter Monday	Mon 9 April	Mon 24 March	Mon 13 April
Anzac Day	Wed 25 April	Fri 25 April	Sat 25 April
Queen's Birthday	Mon 11 June	Mon 9 June	Mon 8 June
Melbourne Cup Day (metro area only)	Tue 6 November	Tue 4 November	Tue 3 November
Christmas Day	Tue 25 December	Thu 25 December	Fri 25 December
Boxing Day	Wed 26 December	Fri 26 December	Sat 26 December

Business Victoria, 2008, *Victorian Public Holidays and Daylight Saving,* Small Business Victoria: Information
Sheet.<*http://www.business.vic.gov.au/busvicwr/_assets/main/lib60208/victorian_public_holidays_an d_daylight_saving_time.pdf*>

Using the above list, and data recorded for those travel dates was filtered out of the VISTA07 results.

<u>School Holidays</u>

The typical school term dates for 2007 and 2008 were used to compile a list of school holidays

As private schools account for approximately 30 % of primary school enrolments, and 40% of secondary enrolments (ABS, 2009), a review of the school term dates in 2011 for a number of private schools was completed in order to try and better understand the scale of variation of the school term from the public school system.

A summary of the findings is listed below:

- All schools appear to begin first term around the same time
- The break at the end of first term appears to begin and end at approximately the same time for all schools
- The break at the end of second term varied significantly, with some schools ending term a week earlier, and some schools beginning third term a week later
- At the end of third term, some schools finish a week earlier, but all schools seem to begin fourth term around the same time
- Some schools finish as early as first week in December, while other schools finish the year a week before Christmas

These findings were applied to the typical school term dates for 2007 and 2008, and the resultant school holiday periods were filtered out of the results.

A list of the dates considered to be school holidays is shown below:

- 23/06/2007 until 22/07/2007
- 15/09/2007 until 7/10/2007
- 1/12/2007 until 28/01/2008
- 21/03/2008 until 6/04/2008

Appendix B – Definition of Zenith Activities and Trip Purposes

In the Zenith model, resident travel is related to the demand for the following 9 <u>activities</u>:

- Being at home
- Work (white collar)
- Work (blue collar)
- Education (primary)
- Education (secondary)
- Education (tertiary)
- Shopping / personal business
- Recreation / social
- Serve passenger / other (e.g. dropping someone off)

In order to build a model based on this set of activities, the locations visited by each VISTA07 respondent were each assigned a Zenith activity.

In the VISTA07 survey, the respondent was asked to choose or described a purpose (i.e. a reason) for visiting each location; examples include work, education, at home, buy something, and social.

Furthermore, each respondent was asked to report on their,

- Employment status ([full time, part time, casual], occupation, industry), and
- Studying status (primary, secondary, full time tertiary, part time tertiary)

The Zenith activity was inferred then by combining the recorded purpose with the employment and studying status of the respondent. The mapping is shown in Table 45 below. The VISTA07 database fields are shown in parentheses.

VISTA07 Purpose (PURP1)	Study Status (STUDYING)	Occupation (ANZSCO1)	Zenith Activity
Home			Being at Home
Work related		[1,2,4,5,6]	Work (white collar)
		[3,7,8]	Work (blue collar)
Social			Recreation / social
Recreation			Recreation / social
Buy something			Shopping / personal business
Personal business			Shopping / personal business
Accompany Someone			Serve passenger / other
Pickup/Deliver Something			Serve passenger / other
Pickup/Dropoff Someone			Serve passenger / other
Other Purpose			Serve passenger / other
Education	Primary		Home based education (primary)
	Secondary		Home based education (secondary)
	Tertiary		Home based education (tertiary)

Table 45 - Derivation of Zenith Activity from VISTA07 survey

Note that white and blue collar have been defined using ANZSCO1 as follows in Table 46 below.

ANZSCO1 classification	White / blue
1. Managers	White
2. Professionals	White
3. Technicians and Trades Workers	Blue
4. Community and Personal Service Workers	White
5. Clerical and Administrative Workers	White
6. Sales Workers	White
7. Machinery Operators and Drivers	Blue
8. Labourers	Blue

Table 46 - Definition of White and Blue Collar (using ANZSCO1)

Each unique pair of activities constitutes a trip purpose; for example, travel between the activities: "Being at home", and "Shopping / personal business", (in either direction) is allocated the trip purpose: "home based shopping / personal business". Note that it doesn't matter whether the trip is from home *to* shopping, or from shopping *to* home; the trip is still a "home based shopping" trip. In this case, the word "based" should <u>not</u> be taken to mean "to".

The resident trip purposes in the Zenith model are:

<u>Home Based</u>

- Home based work (white collar)
- Home based work (blue collar)
- Home based education (primary)
- Home based education (secondary)
- Home based education (tertiary)
- Home based shopping / personal business
- Home based recreation / social
- Home based serve passenger / other

<u>Non-home based</u>
- Work based work
- Work based shopping
- Work based other
- Shopping based shopping
- Shopping based other
- Other non-home based

Note that in the non-home based trip purposes, some level of grouping has occurred:

For example, "Work based other" is the combination of the following activity pairs:

- [Work, Education (primary)]
- [Work, Education (secondary)]
- [Work, Education (tertiary)]
- [Work, Recreation / social]
- [Work, Serve Passenger / Other]

Grouping is required where there is insufficient sample size in the household travel survey to estimate separate models for each trip purpose.

The full list of activity pairs, and their corresponding Zenith trip purpose is provided in Table 47 below.

Activity1	Activity2	Zenith Trip Purpose
Being at home	Work (white collar)	Home based work (white collar)
	Work (blue collar)	Home based work (blue collar)
	Education (primary)	Home based education (primary)
	Education (secondary)	Home based education (secondary)
	Education (tertiary)	Home based education (tertiary)
	Shopping / personal business	Home based shopping / personal business
	Recreation / social	Home based recreation / social
	Serve passenger / other	Home based serve passenger / other
Work (white collar) OR Work (blue collar)	Work (white collar)	Work based work
	Work (blue collar)	Work based work
	Education (primary)	Work based other
	Education (secondary)	Work based other
	Education (tertiary)	Work based other
	Shopping / personal business	Work based shopping
	Recreation / social	Work based other
	Serve passenger / other	Work based other
Shopping / personal business	Education (primary)	Shopping based other
	Education (secondary)	Shopping based other
	Education (tertiary)	Shopping based other
	Shopping / personal business	Shopping based shopping
	Recreation / social	Shopping based other
	Serve passenger / other	Shopping based other
Education (primary) OR Education (secondary) OR Education (tertiary) OR Recreation / social OR Serve passenger / other	Education (primary)	Other non-home based
	Education (secondary)	Other non-home based
	Education (tertiary)	Other non-home based
	Recreation / social	Other non-home based
	Serve passenger / other	Other non-home based

Table 47 - Zenith Trip Purpose Definitions

Appendix C – Definition of Zenith Demographic Variables

The Zenith model currently describes households according to 7 characteristics:

- Household size
- Number of white collar workers
- Number of blue collar workers
- Number of dependants aged 0 to 17
- Number of dependants aged 18 to 64
- Number of dependants aged 65 and over
- Number of cars (excludes motor cycles)

Note that the person categories (white collar worker, blue collar worker, dependant aged 0 to 17, dependant aged 18 to 64 and dependant aged 65 and over) are mutually exclusive. A person cannot be both a dependant and a worker.

VLC does not propose to change the Zenith household classification at this stage, though other classifications have been explored, and may be implemented at a later stage when forecasting issues are explored (as any classification of people / households must be easily forecast, to feed into future year models).

In order to re-estimate the trip generation model, each surveyed household in VISTA07 was classified according to the above variables. To do this, each person had to be classified as a white collar worker, blue collar worker, dependant aged 0 to 17, dependant aged 18 to 64 or dependant aged 65 and over.

This was done using a combination of the respondent's recorded participation in various activities, including :
- Employment (full time, part time, casual)
- Studies (primary, secondary, full time tertiary, part time tertiary)
- Other activities (not yet at school, employed, home duties, retired).

Some of these categories are not mutually exclusive. For example, it is possible to be employed and be a student. Because of this, a set of rules must be applied when classifying people as either workers or dependants.

The rules are defined as follows:

```
1. Primary school student                =>      Dependant
2. Secondary school student              =>      Dependant
3. Full time worker                      =>      Worker
4. Full time tertiary                    =>      Dependant
5. Part time tertiary                    =>      Dependant
6. Part time / casual worker             =>      Worker
7. Home duties / Retired / Unemployed   =>     Dependant
```

The rules are applied in the order listed above. So, a person who is a part time tertiary student, and a part time worker, is classified as a dependant.

Dependants are then classified according to their age: 0 to 17, 18 to 64, or 65 and over. A further breakdown of 18 to 64 into 18 to 24 and 25 to 64 may be considered as a way of improving the trip generation model for tertiary education. However, we may favour a more descriptive and explanatory set of person types, once forecasting considerations are settled.

An alternative classification (which is a candidate for inclusion at a later stage), includes:

- Full time white collar
- Part time white collar
- Full time blue collar
- Part time blue collar
- Not yet at school
- Primary school
- Secondary school
- Full time tertiary
- Part time tertiary
- Home duties
- Unemployed
- Retired
-

A further breakdown of white collar into "with tie, and without tie" is also up for consideration.

Lastly, the number of cars variable is derived by subtracting the motorbikes [MBIKES] from total vehicles [TOTALVEHS]. Motorbikes are removed because the ABS Census does not collect information about motorbike ownership, making the inclusion of motorbikes in the model impractical.

Appendix D – Derivation of Household, Person and Trip Weights

Household, person and trip weights play an important role in the estimation and validation of the trip generation model.

Household and person weights aim to correct for spatial and demographic biases in the sample.

Trip weights aim to correct for some types of systematic under reporting of travel; specifically, under reporting caused by proxy reporting, and delays between the respondent's travel day, and the day on which the survey forms were completed.

This section describes their derivation and application.

D1. Household and Person Weights

The VISTA07 sample is not designed to be demographically or spatially representative; it will over and under sample certain demographics and regions. However, it is possible (using the ABS Census 2006, or any other Census for that matter) to assign households and person "weights", which can correct for many types of demographic and spatial bias.   It is the role of the household and person weights to correct for sample bias.

As the Zenith trip generation model is household based, household weights are used as "weights" to the regression. The effect is that households with larger weights are assigned greater importance when estimating model parameters.

The Urban Transport Institute (TUTI) has derived a set of household and person weights, which have been supplied to VLC as part of the VISTA07 database. A brief summary of their methodology is provided below, though for a comprehensive description, see the TUTI report: *"Victorian Integrated Survey of Travel & Activity 2007-08, Survey Procedures and Documentation v1.3".*

TUTI Calculation of Household Weights

Three control variables were used to calculate households weights:

- Home LGA
- Dwelling Type (2 types: Separate House and Other Type)
- Dwelling Ownership (2 types: Owned & Buying, and Renting & Other)

For each combination of Home LGA, Dwelling Type and Dwelling Ownership, the number of surveyed households was compared with the number of households of this type in the ABS Census 2006, with the ratio of these two quantities determining the household weight.

As a result, the weighted households should be consistent with the ABS Census in terms of the number of households of each dwelling type and ownership status for each LGA.

TUTI Calculation of Person Weights

Each person in each household was initially assigned a weight equal to their corresponding household weight. Individual person weights were then adjusted such that the weighted persons were spatially and demographically representative of the person types found in the ABS Census 2006.

Three control variables were used to adjust person weights:

- Home LGA
- Gender (2 types: Male and Female)
- Age Group (18 groups: 5-year groupings from 0-4 up to 85+)

As a result, the weighted persons should be consistent with the ABS Census 2006 in terms of the number of people of each gender and age group for each LGA.

The TUTI household weight does not take into consideration the demographic characteristics of its inhabitants; instead, demography is part of the person weight. Because of this, VLC has constructed an alternative household weight, which does take into account the demography of the household members. This alternative weight was calculated by taking the average of the person weights of all members of a household. Under this alternative approach, a household whose members come from under sampled demographic groups (in terms of gender / age) will be assigned a larger household weight.

D2. Trip Weights

The household and person weights described in the previous section are designed to ensure that the weighted survey is spatially and demographically representative. TUTI also calculated trip weights which were designed to correct for certain types of under reporting of travel.

In their report: *"VISTA07 Survey Procedures and Documentation"*, TUTI discuss three types of non-reporting of travel:

1. Deliberate non-reporting of travel, "either because they thought they were unimportant or because they wanted to minimise the effort in completing the travel diary",
2. Under reporting due to "proxy reporting", where the travel diary of an individual is filled out by another household member. The other household member may not have full knowledge of the individual's travel, and
3. Under reporting due to forgetfulness or oversight, which is more likely to occur when there is a significant delay between the travel day and when the travel diary is completed.

As part of the survey, TUTI collected information on proxy reporting, as well as any lag between the travel day, and the day when the survey form was completed. This information has been used to correct for items 2 and 3 above.

An analysis of the survey responses found that travel diaries filled out by proxy exhibited lower trip rates on average. They also found that travel diaries not completed on the travel day exhibited lower average trip rates.

There is the potential, of course, for this to be due to demographic factors, rather than under-reporting. For example, it could be that people who do not fill out the form themselves (e.g. young children), do not make as many trips. It may also be the case that "busy" people (potentially those who make many trips) are less likely to find time to complete the form on the travel day, and may wait until the weekend.

To account for this, the effect was explored for different groupings of age and gender to see if the effect was present within each demographic group.

As a result, adjustment factors were calculated for each combination of age, gender, travel mode and trip purpose (home based, and non-home based). In each demographic category, those who filled the form out themselves and on the travel day were considered to be the point of truth, with trip rate adjustment factors calculated relative to this group.

From this analysis, a series of factors have been derived which can grow the travel reported in VISTA07 to a more realistic level.

A limitation of this approach is that the factors act to increase the travel made by those who did actually report trips, but do not apply to those people who didn't travel. That is, after the application of the trip weights, those who did report travel now travel *more*, while those who didn't report any trips still don't travel. One might counter that most people will report *some travel*, but the factors are separately calculated for two trip purposes (home based and non-home based), and for four modes (car driver, car passenger, public transport and walk / cycle). Most people will report no trips for most of the eight categories.

The raising of this limitation is in no way a criticism of the approach; attempting to impute travel for those who report no trips is complex. Furthermore, given that the Zenith model is currently an aggregate model (travel is a continuous quantity which is not attached to any specific person or household), the number of trips predicted for a household is not of great importance, provided that

the total number of trips for a travel zone is accurately predicted. Therefore, the limitation should not significantly bias the Zenith trip generation model.