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Improving a traditional 4-step transport model with a Departure Time Choice model component

Pedro Camargo[1], Tim Spalding[1], Aaron Alaimo[1]

[1]Veitch Lister Consulting

200 Mary Street, Brisbane, QLD 4000

Email for correspondence: pedro.camargo@veitchlister.com.au

Abstract

Increase in congestion in all major Australian cities and a perceived expansion of the peak periods has suggested that peak-spreading is already happening in those cities. This paper summarizes an effort to demonstrate that this effect is a reality in Australia and a modelling framework to augment a traditional 4-step model with a departure time choice sub-component. Model estimation and validation results are also presented.

1. Introduction

Departure time choice (DTC) is a necessary model component/feature when dealing with growing congestion and the verified trend of people changing their departure time to avoid excessive congestion, which is commonly referred to as "peak spreading".

Research undertaken by Veitch Lister Consulting into peak spreading in Victoria between 1994 and 2010 indicated that persons travelling for longer than 30km tend to adapt their departure time most readily. For trips between 10km and 30km travellers have also revealed a significant shift towards earlier departures. This is shown on Figure 1.

As the population in Melbourne is expected to increase significantly in the future, leading to increased congestion, and resulting in greater peak spreading, it is necessary to have a transport model that reflects this behaviour, especially when analysing the impact of new city-shaping infrastructure.

A clear need for DTC models, however, has only been established recently in Australia, and the majority of Australian models still do not include this capability. In order to overcome this issue, we have developed at DTC model component to augment Zenith's[1] 4-step model and have it reflect this peak-spreading phenomenon through the use of discrete choice models. It is noteworthy, however, that the DTC model was developed only for car trips, and transit trips will be tackled in the future.

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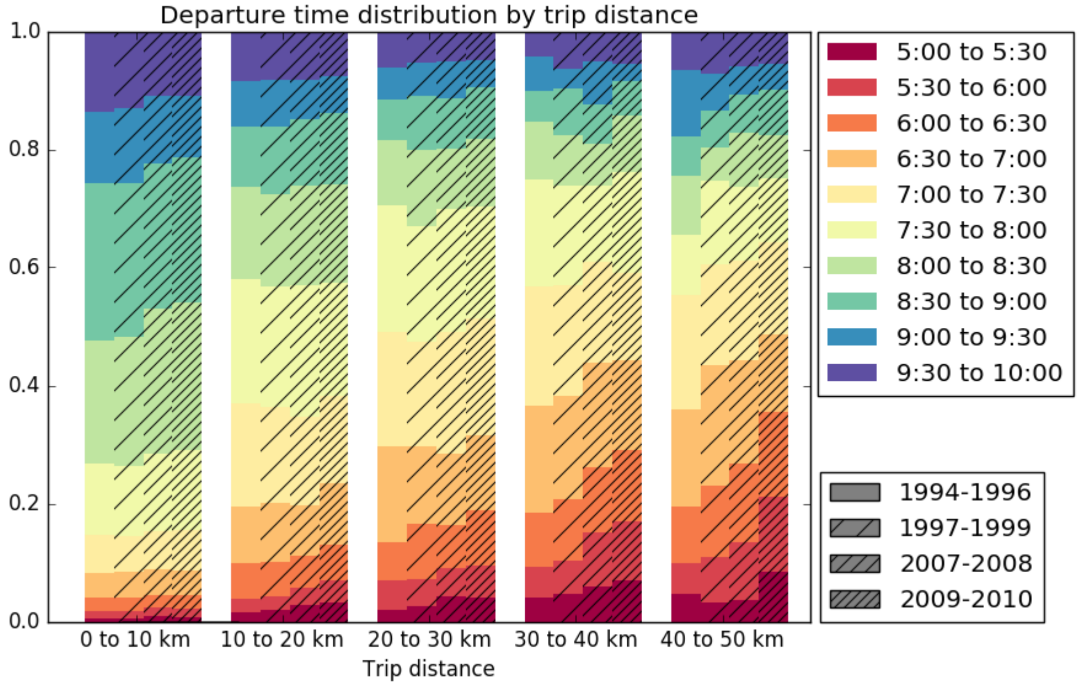
[1] Zenith is Veitch Lister Consulting proprietary transport model. Full information available at www.veitchlister.com.au

Figure 1 Departure time distribution as a function of travel distance in Melbourne



Source: VATS 1994-99 and VISTA 2007-10

2. An augmented model structure

As mentioned before, the Zenith model was conceived as a traditional 4-step model, where each time period was considered to be a fixed share of the daily demand. As this assumption helps define the model structure, augmenting it without a major re-development of the model was a significant challenge, overcome with an approach that includes two levels of time period choice, in the model structure presented in Figure 2.

"Macro" time period allocation

At the "*macro*" level, the model includes four periods:

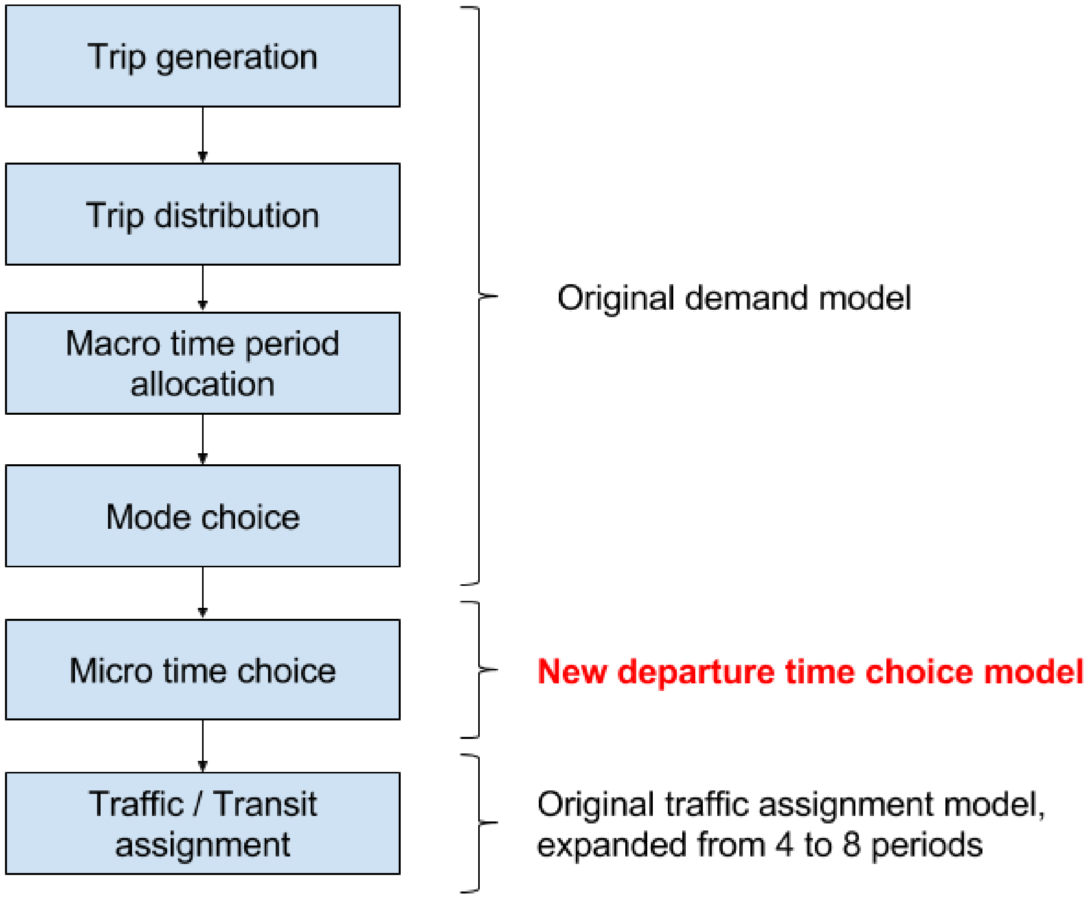
- AM peak (6am - 10am)
- PM peak (3pm - 7pm)
- Inter peak (10am - 3pm)
- Off peak (7pm - 6am)

This four-period structure is identical to the structure currently used in the model, except that the peak periods are increased from two to four hours.

The model uses constant factors (derived from Household Travel Survey) to assign travel to the above four periods. As such, the percentage of daily travel occurring in the four hour AM peak (i.e. 6-10am) will be assumed to remain constant into the future, with the same assumption valid for the PM peak period.

This is consistent with how the model currently works, except that the peaks are extended to four hours.

Figure 2 - Proposed model structure



"Micro" departure time choice

In order to be adapted within the pre-existing Zenith structure, the departure time choice model takes the form of a ***micro-time* departure time choice model**, where trips assigned to a long *macro* peak period (e.g. 6-10am and 3-7pm), are further apportioned to the central peak period or to the two peak shoulders.

Unlike the *macro* time period allocation, the *micro* departure time choice model will **not** assign a fixed percentage of demand to each individual sub-period. Instead, the *micro* departure time choice model will take into account the cost of travelling within each sub-period, and use it to determine the percentage of people who travel in each sub-period. As a result, when travel costs increase in the peak of the peak (e.g. 7-9am), some demand would shift to the peak shoulders (e.g. 6-7am).

As depicted in the model structure on Figure 2, the departure time choice models will be applied after the current demand model, which implies small changes to how the demand model interacts with traffic / transit assignment. The proposed model structure was considered superior to other alternatives evaluated, and will provide clear improvements to current transport modelling practice in Melbourne and other cities where this framework will be applied.

It is noteworthy, however, that the resulting model will have all the micro-time periods traffic assigned to the network, effectively doubling the number of periods being assigned, but the increase in run time was considered small when compared to the increase capability of the model to answer new policy questions.

In turn, these models are only being estimated for personal auto trips and will be estimated within a simple Multinomial Logit (MNL) framework, as the use of more complex model frameworks would require a full re-development of the entire model.

3. Departure time choice in the literature

The literature review conducted for the development of this model was focused exclusively on the estimation and application of departure time choice models, and did not cover transportation modelling and discrete choice modelling in broader terms. For a more complete picture of the role of departure time choice models, please refer to (Ortúzar & Willumsen 2011), and (Train 2009) for a rigorous yet applied description of discrete choice models, including the MNL.

Departure time modelling was first studied by (Vickrey 1969), and has been a topic of research within a discrete choice framework for over three decades, often related to research on traffic assignment equilibrium, as in (Mahmassani & Chang 1986) and (Ran et al. 1996).

In the last two decades, however, most of the focus of the analysis of departure time choice has revolved around tour-based and activity-based models, (Ettema & Timmermans 2003; Vovsha & Bradley 2004), on applications of less conventional choice models, such as continuous cross-nested models (Lemp et al. 2010) and on pricing analysis, such as (Ozbay & Yanmaz-Tuzel 2008; Saleh & Farrell 2005).

Further, the modelling of micro departure time choice is more often done considering household and activity time window restrictions, as some activities have much stricter times to start and to end. This idea has permeated this field since the original work of (Vickrey 1969), and is clearly delineated by (Palma et al. 2003).

Another topic that has entered departure time choice research with increasing importance is the matter of travel time reliability. One of its earliest mentions is already 30 years old (Mahmassani & Chang 1986), but it was only many years later that (Lemp et al. 2010) formally included reliability measures in a departure time choice model. As it is common practice in reliability-related studies, (Lemp et al. 2010) measured reliability as the standard deviation of the expected travel time. Unfortunately it is not possible to obtain this standard deviation from the static traffic assignment algorithms commonly used in strategic transport models.

4. Data

There are two main sources of data for model estimation: Firstly, revealed departure time choice data, in the shape of household travel surveys and cost skims[2] from our transport models. A second household travel survey, conducted more recently than the one used for model estimation, is used for model validation.

4.1 Revealed behaviour data

The data source used for model estimation is the VISTA survey for 2007 through 2010, which is the data source utilized by VLC for estimating its current Zenith model for Melbourne.

[2] All costs measured in AUD cents

4.2 Network costs

The Zenith model is setup to provide a number of measures related to travel cost throughout the network. While several of these measures are not particularly relevant to this model development, an array of other measures warranted consideration as explanatory variables in these models, as follows:

- Travel time: Travel time (in vehicle) between zones
- Toll cost: Average toll expenditure between zones[3]
- Out of pocket cost: Average tolls expenditure plus the fuel cost associated with running the vehicle for a given distance between zones

4.2.1 Network cost production

In order to obtain the network costs for each time period, for model estimation, we needed to perform traffic assignments for each of the 'new' time periods (i.e. the peak shoulders), which were previously not explicitly included in Zenith. In order to produce temporary vehicle matrices for each peak shoulder hour, we proceeded to factor the existing Zenith peak two hour matrices to their respective shoulders.

To support this factoring process, we examined surveyed travel time data from VISTA by SA1. Each surveyed trip was sorted into a time period, and categorised based on the distance travelled. Only car driver trips occurring between 6 and 10am or 3 and 7pm were considered for this analysis.

The trip distances utilized were obtained from a converged 2011 Zenith model of Victoria for each origin-destination pair of travel zones, and were aggregated to SA1 level to match the VISTA datasets. Each surveyed trip was assigned a trip distance based on the trip’s SA1 origin and destination from this modelled trip distance and classified into five kilometre distance brackets. For example, a trip 12.4km long was classified in the 10-15km bracket.

For example, this data shows that 62% of trips shorter than 5km between 6 and 10am occurred between 7 and 9 am, while only 6% occurred between 6 and 7 am, as shown on Figure 3 below.

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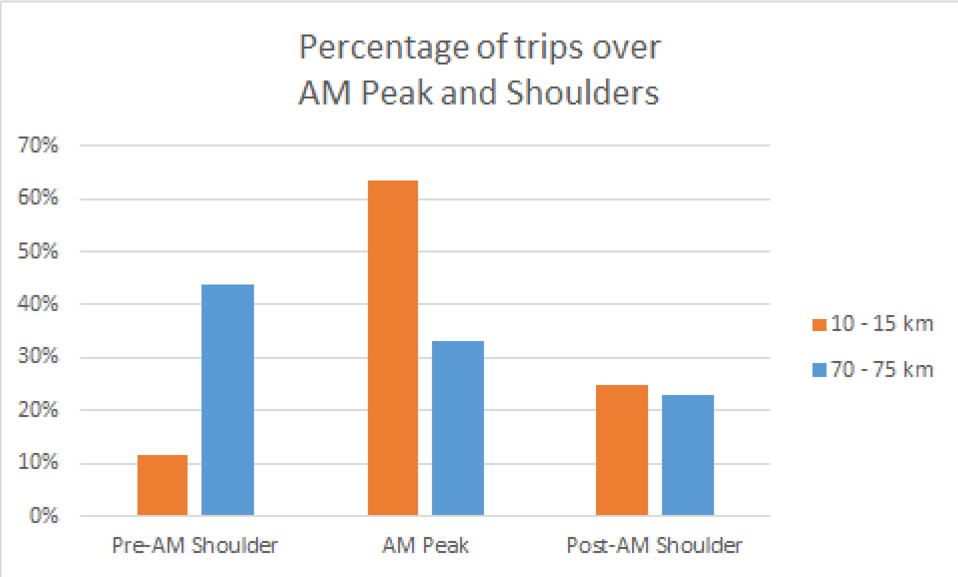
[3] The tolls do not vary from one time period to the other, but the proportion of people that take the tolls during the peak is much higher. As a consequence, the average toll paid by travellers between a given origin and destination is higher during the peak periods and lower in the shoulders and non-peak periods

Figure 3 - Percentage of trips in the AM peak periods for different trip lengths



With these factors in hand, shoulder assignable matrices were created from Zenith AM Peak and PM Peak matrices. Each origin-destination pair from the Zenith peak matrices were categorised into the 5km brackets, and from that a proportion of trips were transposed into the shoulder time periods based on the proportion of trips per time period and distance class, as tabled above.

These shoulder time period trip matrices were then assigned to a network using Zenith and validated against counts, resulting in cost outputs for each shoulder time period.

5. Model specification

The most common model structures for departure time choice models in the literature include basic demographic characteristics of travellers in their formulations, particularly concerning income, gender and existence of children in the family (Ettema & Timmermans 2003), (Mannering & Hamed 1990) and (Ozbay & Yanmaz-Tuzel 2008). These models were developed under the premise of very disaggregate travel demand models, which is not the case of the current generation of Zenith models.

On the other hand, Zenith provides a very disaggregate set of trip purposes, surpassing to a great degree the work found in the literature in this aspect, which we found to be an extremely relevant tool for implementing DTC. This will be highlighted in the initial sample results section.

4.3 Model specification assumptions

Two key simplifications are made when specifying the utility functions for each model estimated, including:

1. Cost parameters for a peak period (AM or PM) are generic (are the same for the peak core and its shoulders). We believe that such assumption is conservative and necessary, noting that there is no consensus on this topic in the literature, with other authors having chosen to not make this same assumption, e.g. (Ozbay & Yanmaz-Tuzel 2008).

2. Cost parameters can vary across trip purposes and across time periods (AM Vs. PM)

4.4 Preferred model structure

After reviewing the available literature on departure time choice and applying the considerations aforementioned, we have opted for a fairly generic model form that allows for the inclusion of an arbitrary number of cost parameters and full differentiation of behaviour, including different cost parameters for different travel purposes, as shown in the equation below,

$$V_p = ASC_p + \sum_{c \in costs} \beta_c * C_{c,p} + \sum_{q \in purposes} \beta_q * X_q + \sum_{q \in purposes} \sum_{c \in costs} \beta_{q,c} * C_{c,p} * X_q$$

Where

- V_p is the representative utility[4] for period p (pre-shoulder, peak period, post shoulder)

The parameters that need to be estimated are

- ASC_p is the Alternative Specific Constant,
- β_c is the model parameter for one particular cost C (constant across alternatives)
- β_q is the model parameter for trips of a certain purpose q
- $\beta_{q,c}$ is the model parameter for one particular cost C when the trip has a purpose q

And the characteristics of the alternatives and travel segments are:

- X_q Dummy variable with a value of 1 if a particular trip is for purpose q and 0 otherwise
- $C_{c,p}$ Cost c for alternative p

From the model specification it follows that the consideration of all possible parameters in the proposed functional form would be equivalent of having separate models estimated for each travel purpose. However, it was anticipated that there may not be enough variation in the sample for some travel purposes to allow for robust model estimation, therefore some aggregation was required.

A few other assumptions are needed to understand to the models, including:

- The Alternative Specific Constant for the peak period was normalized to zero
- When β parameters that multiply the dummy variables for different trip purposes are included in the model, one of such β was normalised to zero, even though it is presented with an *estimated* value of zero

When β parameters that multiply the cost parameters for specific purposes are included in the model, one of such β was normalised to zero, even though it is presented with an *estimated* value of zero.

4.5 On the Value of Time

As the cost of tolls is expected to be relevant in cities with urban tolled routes, including a measure of toll cost in the departure time choice to measure possible impacts of different toll prices was deemed necessary. As a consequence of having a measure of cost and a

[4] For a formal definition, please refer to (Train 2009), page 15

measure of time (main driver for departure time choice change) in these models, a Value of Time (VoT) would be implied.

During the model estimation process, we made several attempts to derive a VoT from parameters estimated for time and monetary costs, including experimenting with different trip purpose aggregation and with different measures of monetary cost (i.e. out-of-pocket and toll). However, these experiments did not yield reasonable estimates for VoT.

As the estimation of VoT was unsuccessful, asserting a VoT was the only possible alternative, and such a value is expected to come from surveys designed specifically for this purpose. For the development described on this paper, however, a VoT of AUD25/h was asserted, which is in line with the VoT used in many transportation modelling exercises in Australia. When a new estimate for VoT becomes available, the model estimation will need to be updated, although no major parameter changes are to be expected if the new VoT does not deviate too much from the asserted value.

6. Results for the AM peak

The process of developing econometric models passes necessarily through the experimentation of a large number of model specifications, which allows for the discovery of unexpected relationships and provides us an opportunity to refine our understanding of the departure time decision process. The results for these tests, however, are not presented in this paper, and we also decided to present only the models estimated for AM peak, as there are no significant differences between these models and those estimated for the PM peak aside from the parameters themselves.

Among all tests performed, the most informative, and worthy of mentioning, was the estimation of purpose-specific models, which provided a clear picture of the specific sensitivity to transport time/cost for each travel purpose, and informed the model aggregation ultimately used.

As previously discussed, the simultaneous use of time and cost variables in the majority of models we tested yielded non-reasonable estimates of VoT. As a consequence, and driven by the desire to have toll prices as a decision variable for departure time choice, we decided to utilize a measure of travel cost that considers travel time and toll cost weighted by the pre-established VoT, formulated as below:

$$\text{Cost} = \text{Time} + \frac{\text{Toll}}{VoT}$$

Further, in order to maintain consistency of approach throughout the model, the same trip purpose aggregation was used for both the AM and PM peaks. This aggregation is the following:

Table 1 – Tri purpose aggregation[5]

Aggregate purpose	Included purposes
Education	HPR - Home-based Primary education HSE - Home Based Secondary education
Work	HWW - Home Based Work white collar HWB - Home Based Work blue collar WBW - Work Based Work

[5] Home-based Primary education, Home Based Secondary education

Aggregate purpose	Included purposes
	HTE - Home Based Tertiary education
Shopping	HBS - Home Based Shopping SBS – Shopping Based Shopping WBS – Work Based Shopping HBR - Home Based
Other	HBO - Home Based SBO – Shopping Based Other WBO – Work Based Other ONHB – Other Non-Home Based

There are a few characteristics of this aggregation that should be noted. The first one is that the non-home-based purposes are aggregated based on their destination purposes (eg. Work Based Shopping (WBS) is a shopping trip). The second item to note is that trips for tertiary education (HTE) are aggregated with *Work* (White and Blue collar) trips, rather than with *Education* trips and recreation trips are in the group of *shopping* trips instead in the *other* category.

4.6 Estimation results

For the AM peak, the final models are presented on Table 2 through Table 5, below. The complete estimation reports can be found in the appendices of this paper.

Table 2 – AM Peak Model for education trips

Variable	Parameter values		
	Pre-AM	AM	Post-AM
Time + Toll		-0.02531	
Purpose Dummies			
Primary study	-5.33906	-	-3.13210
Secondary study	-5.89892	-	-3.68476

Table 3 – AM Peak Model for work trips

Variable	Parameter values		
	Pre-AM	AM	Post-AM
Time + Toll		-0.01692	
Purpose Dummies			
Home-based Tertiary	-4.66054	-	-0.81568
Home-Based Blue Collar	-0.62334	-	-2.13617
Work-based Work	-2.46882	-	0.12168
Home-Based White Collar	-2.04633	-	-1.86942

Table 4 – AM Peak Model for shopping trips

Variable	Parameter values		
	Pre-AM	AM	Post-AM
Time + Toll		-0.00489	
Purpose Dummies			
Home Based Recreation	-1.45002	-	-0.13933
Home Based Shopping	-2.03201	-	0.21044
Shopping-based Shopping	-2.65389	-	1.05762
Work-Based Shopping	-1.57751	-	-0.69678

Table 5 – AM Peak Model for trips with other purposes

Variable	Parameter values		
	Pre-AM	AM	Post-AM
Time + Toll		-0.05108	
Purpose Dummies			
Home Based Other	-3.32971	-	-1.55734
Other Non-Home-Based	-4.28291	-	-1.44042
Shopping Based Other	-3.86714	-	-0.20121
Work-Based Other	-3.28300	-	-1.30523

It is possible to see that the cost parameters for all the models are substantially different from each other. However, given the also substantial numerical difference between the dummy purposes, it is not reasonable to elaborate on the sensitivity to cost of each model. Instead, we present charts depicting that the overall peak shoulder travel when travelling in either peak is equally cheaper in comparison with the central peak. This analysis is presented from Figure 4 through Figure 7.

Figure 4 – AM peak study travel model sensitivity

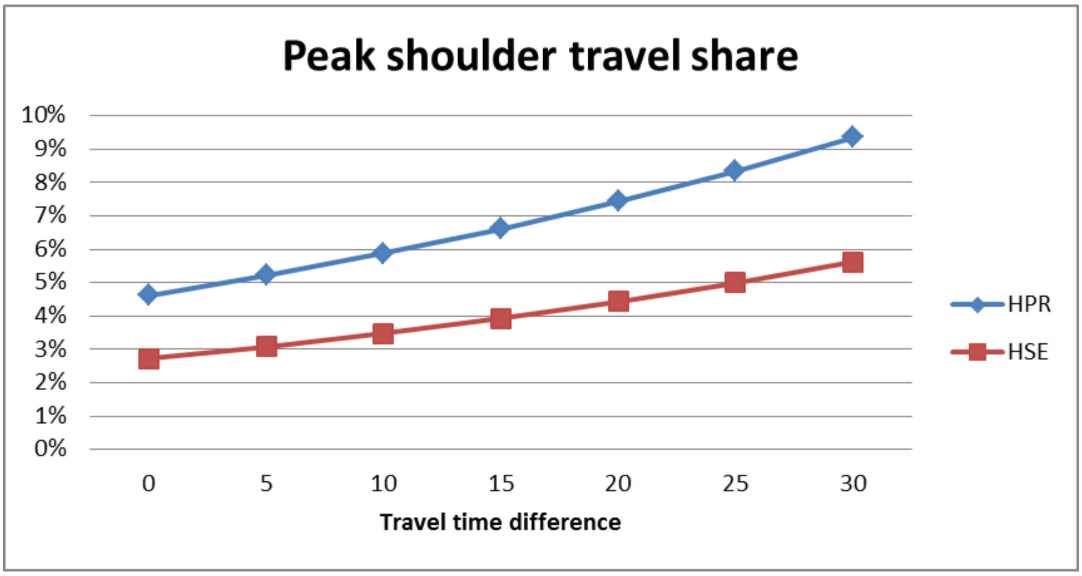


Figure 5 – AM peak work travel model sensitivity

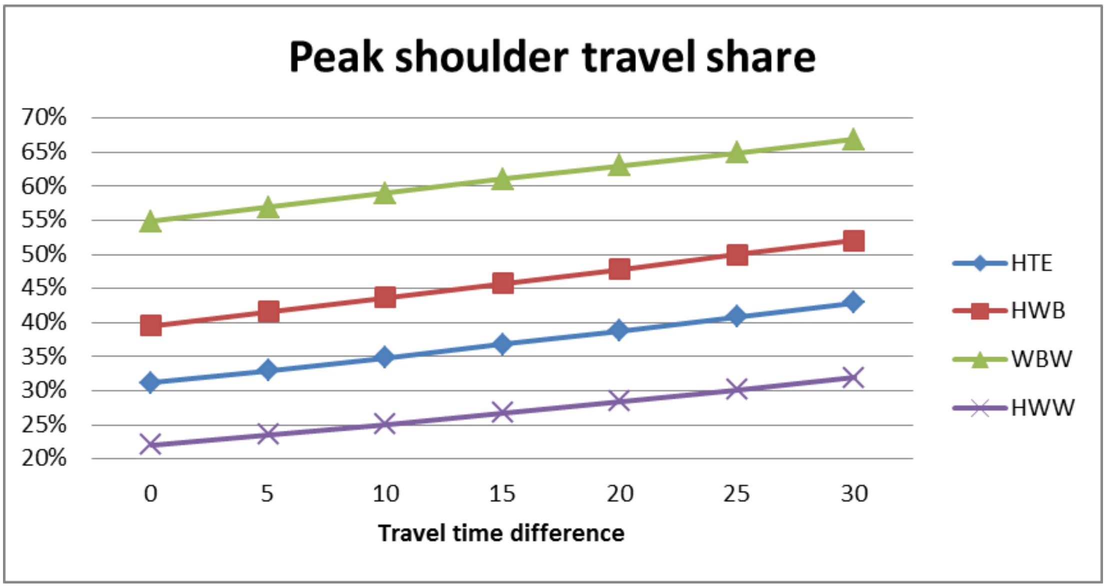


Figure 6 – AM peak shopping travel model sensitivity

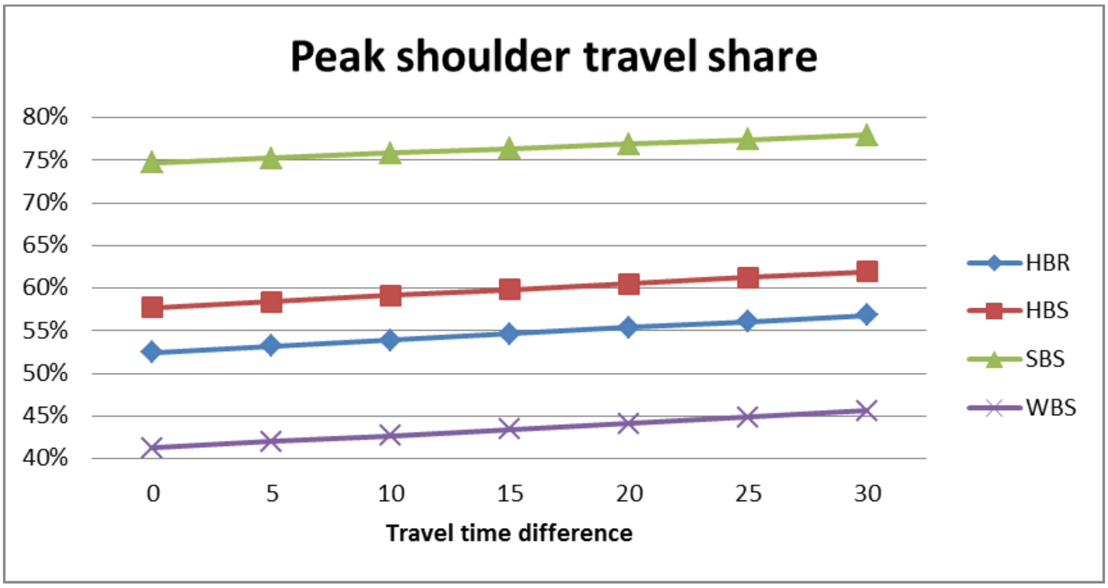
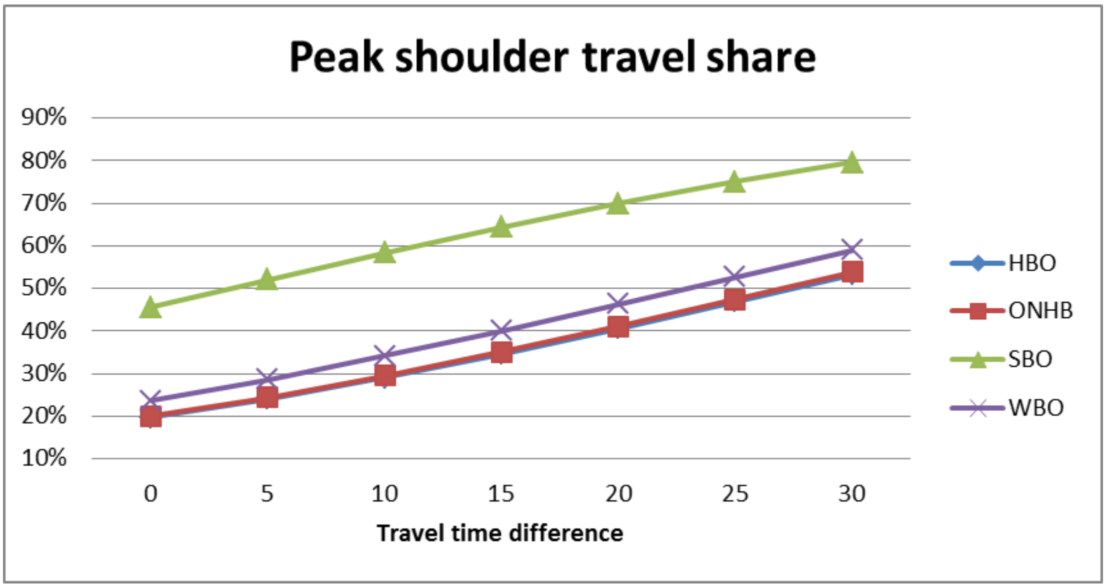


Figure 7 – AM peak other travel model sensitivity



From the sensitivity analysis it can be concluded that trips for a few purposes are much more prone to change their departure time as congestion builds up. As it would be expected, primary and secondary education trips are the least sensitive to congestion in absolute terms, but the peak-shoulder share of trips approximately doubles when the travel time difference between peak and shoulders goes from 0 to 30 minutes.

On the other side of the spectrum, trips for other purposes share on the shoulder periods nearly doubles for home based trips, going to almost 55% when travel time differences in relationship to the peak time is close to 30 minutes.

5. Model validation and conclusions

As mentioned before, the models were estimated using VISTA 07/10 data, and the independent dataset used for validation is the VISTA 12/13 data, which is a critical test for the model parameters obtained and the temporal stability for departure time choice behaviour.

The model validation was performed by applying the estimated model to the validation dataset and comparing the aggregate sub-period share for each trip purpose modelled and for each category of travel time/cost savings in relation to the peak period. Using these parameters, there was not enough sample size to compute the relevant metrics with their associated confidence of interval for all travel purposes, hence only some of them are presented here.

Figure 8 and Figure 9 clearly show that all model results are well within the confidence intervals established, and especially for the aggregate result, the model performance is remarkable.

Figure 8 – AM trips model validation

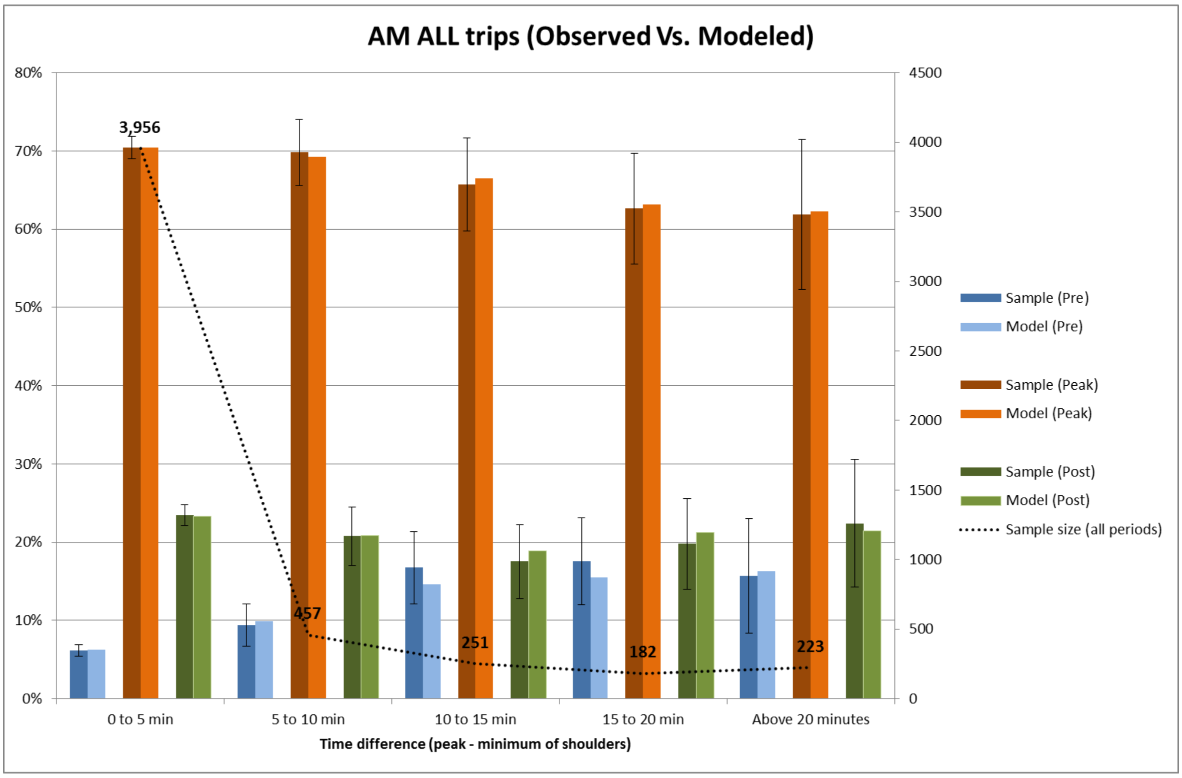
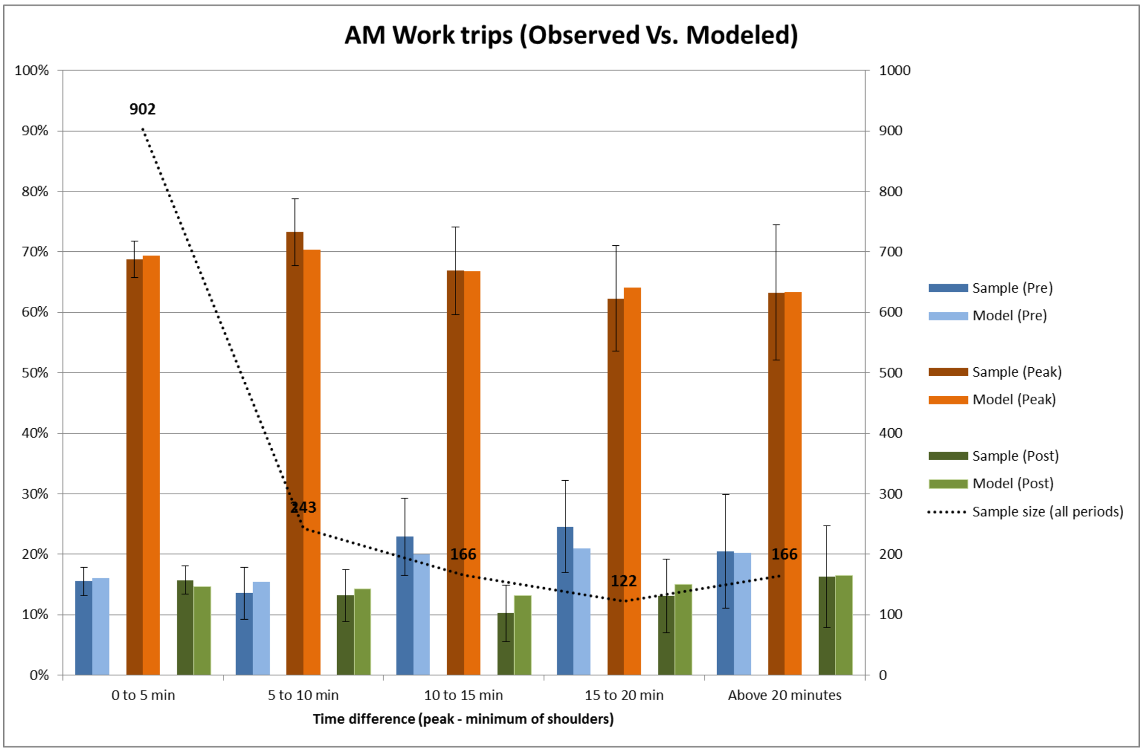


Figure 9– AM Work trips model validation



In this paper we have shown that estimating departure time choice models with the Household travel survey data available in Australian cities is possible and requires only a small percentage of the effort associated with a full model build. The estimation process itself yielded parameter estimates that are significant and efficient from an econometric point of view, and within the expected sensitivity from a more qualitative point of view.

We have also demonstrated the model robustness by validating them against independent data sources, which is vital for building trust on any new modelling practice.

The final model run time increased by approximately 25%, as traffic assignment is not the most time consuming step of this model system and no further full model iterations were required to equilibrate it.

In conclusion, we have demonstrated that augmenting traditional 4-step models with a departure time choice component increases the model relevance when dealing with growing congestion, and it is a very pragmatic way to extend the life of the transport models currently in operation in Australia and New Zealand.

6. References

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7. Appendices

7.1 Biogeme report: Work trips

Estimation report

Number of estimated parameters:	9
Sample size:	9038
Excluded observations:	20713
Init log likelihood:	-9929.258
Final log likelihood:	-6929.049
Likelihood ratio test for the init. model:	6000.417
Rho-square for the init. model:	0.302
Rho-square-bar for the init. model:	0.301
Final gradient norm:	+4.331e-03
Diagnostic:	Convergence reached...
Iterations:	8
Data processing time:	00:00
Run time:	00:01
Nbr of threads:	4

Estimated parameters

Click on the headers of the columns to sort the table [Credits]

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_timetoll	-0.0169	0.00304	-5.56	0.00		0.00308	-5.50	0.00	
Dummy_HTE_Post_AM_Shldr	-0.816	0.130	-6.29	0.00		0.130	-6.28	0.00	
Dummy_HTE_Pre_AM_Shldr	-4.66	0.711	-6.55	0.00		0.709	-6.57	0.00	
Dummy_HWB_Post_AM_Shldr	-2.14	0.0800	-26.72	0.00		0.0802	-26.65	0.00	
Dummy_HWB_Pre_AM_Shldr	-0.623	0.0486	-12.84	0.00		0.0485	-12.85	0.00	
Dummy_HWW_Post_AM_Shldr	-1.87	0.0438	-42.66	0.00		0.0442	-42.32	0.00	
Dummy_HWW_Pre_AM_Shldr	-2.05	0.0492	-41.58	0.00		0.0491	-41.68	0.00	
Dummy_WBW_Post_AM_Shldr	0.122	0.0788	1.54	0.12	*	0.0788	1.54	0.12	*
Dummy_WBW_Pre_AM_Shldr	-2.47	0.201	-12.27	0.00		0.201	-12.29	0.00	

7.2 Biogeme report: Study trips

Estimation report

Number of estimated parameters:	5
Sample size:	3605
Excluded observations:	26146
Init log likelihood:	-3960.497
Final log likelihood:	-668.694
Likelihood ratio test for the init. model:	6583.607
Rho-square for the init. model:	0.831
Rho-square-bar for the init. model:	0.830
Final gradient norm:	+1.703e-04
Diagnostic:	Convergence reached...
Iterations:	8
Data processing time:	00:00
Run time:	00:01
Nbr of threads:	4

Estimated parameters

Click on the headers of the columns to sort the table [Credits]

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_timetoll	-0.0253	0.0389	-0.65	0.51	*	0.0343	-0.74	0.46	*
Dummy_HPR_Post_AM_Shldr	-3.13	0.104	-30.07	0.00		0.102	-30.65	0.00	
Dummy_HPR_Pre_AM_Shldr	-5.34	0.294	-18.18	0.00		0.292	-18.28	0.00	
Dummy_HSE_Post_AM_Shldr	-3.68	0.206	-17.87	0.00		0.206	-17.91	0.00	
Dummy_HSE_Pre_AM_Shldr	-5.90	0.586	-10.06	0.00		0.590	-10.01	0.00	

7.3 Biogeme report: Shopping trips

Estimation report

Number of estimated parameters:	9
Sample size:	5829
Excluded observations:	23922
Init log likelihood:	-6403.811
Final log likelihood:	-5105.969
Likelihood ratio test for the init. model:	2595.685
Rho-square for the init. model:	0.203
Rho-square-bar for the init. model:	0.201
Final gradient norm:	+1.004e-02
Diagnostic:	Convergence reached...
Iterations:	6
Data processing time:	00:00
Run time:	00:01
Nbr of threads:	4

Estimated parameters

Click on the headers of the columns to sort the table [Credits]

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_timetoll	-0.00489	0.00647	-0.76	0.45	*	0.00673	-0.73	0.47	*
Dummy_HBR_Post_AM_Shldr	-0.139	0.0573	-2.43	0.02		0.0575	-2.42	0.02	
Dummy_HBR_Pre_AM_Shldr	-1.45	0.0892	-16.26	0.00		0.0888	-16.33	0.00	
Dummy_HBS_Post_AM_Shldr	0.210	0.0393	5.36	0.00		0.0394	5.34	0.00	
Dummy_HBS_Pre_AM_Shldr	-2.03	0.0841	-24.16	0.00		0.0835	-24.32	0.00	
Dummy_SBS_Post_AM_Shldr	1.06	0.0935	11.31	0.00		0.0935	11.31	0.00	
Dummy_SBS_Pre_AM_Shldr	-2.65	0.312	-8.50	0.00		0.312	-8.50	0.00	
Dummy_WBS_Post_AM_Shldr	-0.697	0.0816	-8.53	0.00		0.0823	-8.46	0.00	
Dummy_WBS_Pre_AM_Shldr	-1.58	0.113	-13.95	0.00		0.112	-14.10	0.00	

7.4 Biogeme report: Other purposes

Estimation report

Number of estimated parameters:	9
Sample size:	11279
Excluded observations:	18472
Init log likelihood:	-12391.248
Final log likelihood:	-6993.707
Likelihood ratio test for the init. model:	10795.082
Rho-square for the init. model:	0.436
Rho-square-bar for the init. model:	0.435
Final gradient norm:	+1.132e-02
Diagnostic:	Convergence reached...
Iterations:	7
Data processing time:	00:00
Run time:	00:02
Nbr of threads:	4

Estimated parameters

Click on the headers of the columns to sort the table [Credits]

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
B_timetoll	-0.0511	0.00547	-9.34	0.00	0.00567	-9.02	0.00
Dummy_HBO_Post_AM_Shldr	-1.56	0.0320	-48.71	0.00	0.0322	-48.32	0.00
Dummy_HBO_Pre_AM_Shldr	-3.33	0.0691	-48.20	0.00	0.0685	-48.63	0.00
Dummy_ONHB_Post_AM_Shldr	-1.44	0.0638	-22.57	0.00	0.0638	-22.58	0.00
Dummy_ONHB_Pre_AM_Shldr	-4.28	0.232	-18.49	0.00	0.230	-18.63	0.00
Dummy_SBO_Post_AM_Shldr	-0.201	0.0626	-3.21	0.00	0.0629	-3.20	0.00
Dummy_SBO_Pre_AM_Shldr	-3.87	0.281	-13.77	0.00	0.280	-13.81	0.00
Dummy_WBO_Post_AM_Shldr	-1.31	0.0668	-19.55	0.00	0.0661	-19.74	0.00
Dummy_WBO_Pre_AM_Shldr	-3.28	0.145	-22.63	0.00	0.147	-22.40	0.00