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Demand for taxi services: New elasticity evidence for a neglected mode.

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TITLE: **Demand for taxi services: New elasticity evidence for a neglected mode.**

ABSTRACT: This paper investigates the factors that influence the choice of, and hence demand for taxis services, a relatively neglected mode in the urban travel task. Given the importance of positioning preferences for taxi services within the broader set of modal options, we develop a modal choice model for all available modes of transport for trips undertaken by individuals or groups of individuals in a number of market segments. A sample of recent trips in Melbourne in 2012 was used to develop segment-specific mode choice models to obtain direct (and cross) elasticities of interest for cost and service level attributes. Given the nonlinear functional form of the way attributes of interest are included in the modal choice models, a simple set of mean elasticity estimates are not behaviourally meaningful; hence a decision support system is developed to enable the calculation of mean elasticity estimates under specific future service and pricing levels. Some specific direct elasticity estimates are provided as the basis of illustrating the magnitudes of elasticity estimates under likely policy settings.

KEY WORDS: ***Taxi; fare elasticities; service elasticities; choice experiment; decision support system.***

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1. Study background

The Victorian Government, in an inquiry into the structure of the Victorian taxi industry in 2012, identified that there currently exists very little information about the demand for taxi services, and that such a lack of information is a serious barrier to understanding the impact of any reforms that the Inquiry recommends.

A critical missing empirical element is relevant evidence on the direct elasticities associated with taxi fares and service levels for specific trip purposes. International evidence is limited, and what is available is quite disparate in evidence and methods used. Table 1 summarises the few elasticities that are identified from a literature review[1]. The demand dimension is predominantly the number of trips, but there is also evidence related to kilometres travelled and revenue received. There is a mixture of one time series (revealed preference) study and three stated preference studies, with five studies not providing information on the nature of the data. The time series data is aggregate annual data and the stated preference (SP) data is survey data on specific taxi trips. It appears that no effort was made in the SP studies to calibrate the models to known market modal shares or total trips, which is necessary to be able to obtain meaningful estimates of elasticities. For the number of trips, the evidence on fares ranges from -0.23 to -1.75, with the majority of the mean estimates in the -0.5 to -1.0 band. Evidence on service elasticities, defined by in-vehicle time and waiting time is particularly scarce, with only two studies reporting empirical estimates, with substantial variation by trip purpose (a range of -0.15 to -0.58) and over all purposes (e.g. -0.10). The majority of the studies are over 20 years old, with some undertaken over 45 years ago. There is considerable ambiguity about the methods used and the reliability of the mean estimates, suggesting the need for a revisit to establish a set of estimates that are not only current, but also are based on state of the art econometric and data collection methods.

In response to the dearth of evidence, and the difficulty in selecting indicative estimates from available sources for the Victorian Taxi industry inquiry, this paper presents results of a study undertaken for the Victorian Inquiry to gather and analyse data to identify the key drivers of demand for taxis[2]. Mixed multinomial logit choice models were estimated using stated choice (SC) data, with parameter estimates and data embedded in a decision support system (DSS) that used the full preference distributions for each parameter estimate to investigate 'what if' scenarios in respect of traveller responses to taxi fare and service level changes. Implied elasticities are then obtained from the before and after evidence.

The paper is set out as follows. Section 2 provides an overview of the empirical approach, whilst Section 3 provides a brief summary of the stated choice data and survey techniques, as well as how such a method is applied. Next, Section 4 outlines how the data collected is analysed and Section 5 discusses the sampling strategy. Section 6 provides information related to the data collected before the model results are presented and discussed in Section 7. A decision support system is introduced in Section 8 with an emphasis on how the utility expressions with preference heterogeneity parameters and data on population modal shares are embedded, and a number of indicate elasticity estimates are presented. Concluding comments are provided in Section 9.

[1] In recognising that many of the reported elasticities in Table 1 are from studies undertaken quite some time ago, we undertook a search of more recent studies, especially those related to airport access mode. To our surprise and disappointment, we could not build on the earlier evidence. For example the report by Gosling (2008) reviewed many US studies on access mode to the airport and does not report a single elasticity.

[2] Hire cars were also considered but the focus of this paper is on taxis.

Table 1: Direct taxi demand elasticities with respect to fare and service

Study	**Location**	**Data**	**Elasticity measure**	**Fare**	**In-vehicle time**	**Waiting time**
Schaller (1999)	New York, USA	Time series (1990-96)	Revenue	-0.22		
Flores-Guri (2003)	New York, USA	Time series (1990-99)	Kilometre driven	-1.05		
Toner (2010)	Four UK cities	Stated Preference (SP)/Transfer Price (collected in 1989-91)	Number of trips	-1.0	-0.10	-0.07
Rouwendal (1998)	the Netherlands	SP (collected in 1997)	Number of trips	All taxi users: -1.14 Business: -0.76 Going out: -1.75 Going to the railway station: -0.69	Business: -0.44 Going out: -0.52 Going to the railway station: -0.35	Business: -0.58 Going out: -0.62 Going to the railway station: -0.48
Beesley (1979)	London, UK	Time series (1951-52)	Kilometres driven	-0.35		
Wong (1971) cited in Frankena and Pautler (1984)	Washington DC, USA	N/A	Number of trips	-1.4		
Applied Economics Associates (1978) cited in Frankena and Pautler (1984)	Seattle, USA	N/A	Number of trips	-1.0		
Kitch *et al.* (1979) cited in Frankena and Pautler (1984)	Chicago	N/A	Number of trips	-0.80		
McGillivray (1979), cited in Frankena and Pautler (1984)	Danville, USA	Time series: 1975-77	Number of trips	-0.60		
Brown and Fitzmaurice (1978) cited in Frankena and Pautler (1984)	21 cities, USA	N/A	Number of trips	-0.80		
Orfeuil and Hivert (1989), cited in BITRE Database	Paris, France	N/A	N/A	-0.50		
Queensland Transport (2000)	Queensland, Australian	N/A	Number of trips	Brisbane: -0.36 Other cities: -0.50		
Booz Allen Hamilton (2003)	Canberra, Australia	SP (collected in 2002)	Number of trips	All taxi users: -0.36 Peak hour: -0.23 Off peak: -0.41	All taxi users: -0.10	

Notes: The original elasticity provided in Schaller (1999) is a revenue elasticity (-0.22) with respect to fare, which is equivalent to a demand (kilometre) elasticity of -1.22. BITRE Database: http://www.bitre.gov.au/tedb/index.aspx. SP methods present individuals with hypothetical scenarios and use the responses supplied to reveal information about the preferences underlying the choices made. TP methods elicit from each respondent the change in an attribute level of their chosen mode which would be just sufficient to cause a change in behaviour" (Toner 2010, p.306).

2. The approach

Although the primary interest is in identifying the role and performance of taxis, it is necessary to consider alternative modes as a way of identifying the contribution of taxis to the overall passenger transport task. To do this requires the development of a modal choice model in which all feasible modal alternatives are assessed as chosen or non-chosen alternatives for a specific trip.

Given that the modal shares for specific trip purposes and user segments are dominated by the car, and the focus of this study is on service levels of taxis, we have to ensure that all modes are studied with a sufficiently large sample to identify the key factors that influence the choices made by individual travellers, be they travelling by themselves or in a group. We are as much interested in non-users, as we are in users of taxis, since their non-use may be a consequence of the cost and service levels offered by taxis. To understand user preferences for taxis in contrast to preferences for car, and public transport modes (including hire cars) and walking, we have to gather data from a sample of individuals who have recently experienced using one or more of the available modes of transport for a specific trip purpose. It is important to note that such trips need not necessarily have been undertaken via a taxi, but that the sampled trips potentially could have used a taxi for access, main linehaul or egress legs of travel. As such, the sample must include individuals from the main user segments that taxis service, such as corporate users, tourists (both international and domestic visitors), and locals undertaking social outings. Furthermore, the role that taxis may play in each segment could be influenced by the timing of the trip (e.g., evenings) and the specific destination (e.g., an airport or nightclub).

Given the lack of revealed preference (RP) data on travel demand for taxis, we use a stated choice (SC) experiment embedded within a larger computed assisted personal survey instrument (CAPI) to obtain an understanding of the key attributes that influence mode choice. Candidate attributes are summarised in Table 2. The SC experiment involves a universal choice set of up to seven modes, but recognises that for most trips, only a few of these modes are available or feasible.

Table 2: An overview of the key attributes

Attributes	Taxi	Hire car	Car	Bus	Tram	Train	Walk
Time to get to main mode (access time) (mins)	×			×	×	×	
Time waiting for main mode (mins)				×	×	×	
Time in main mode (mins)	×	×	×	×	×	×	×
Time to get from main mode to destination (egress time) (mins)	×	×	×	×	×	×	
Level of crowding (% seats occupied, number of people standing)							
Cost or fare ($ per one-way trip)	×	×	×	×	×	×	
Tolls incurred ($)	×	×	×				
Parking cost ($ per day)			×				
Probability of specific wait times occurring	×	×					
Probability of specific trip travel times occurring	×	×	×				
Probability of specific fare payments occurring	×	×					

Figure 1 summarises the eligible trip settings which may include an access mode or a main mode setting. We begin by defining a current or recent trip experience made in the past five days. Knowing this provides data to assist in selecting a specific recent trip that contributes to the quotas selected to ensure sufficient sample sizes for each user segment. Eligible respondents were screened in-scope prior to their participation in the choice experiment.

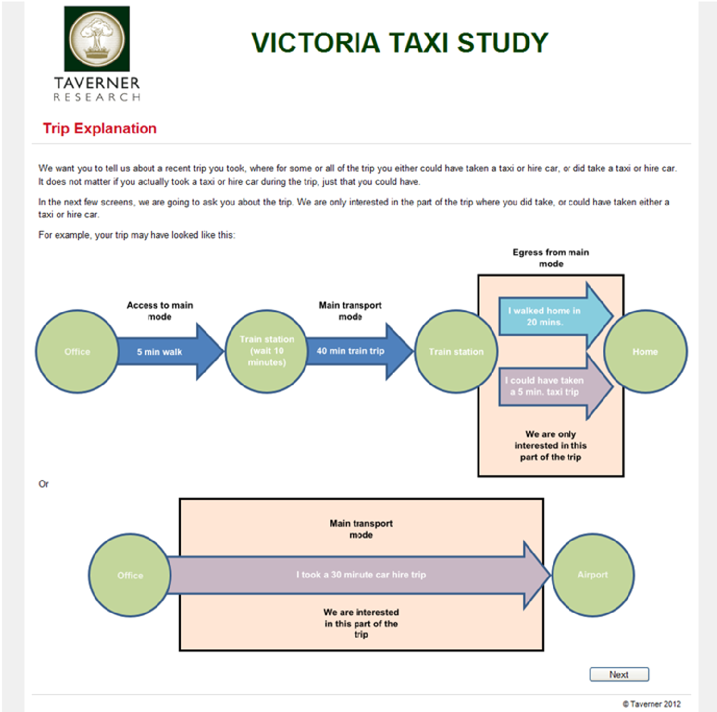

Figure 1: Trip contexts

3. The stated choice experiment

The stated choice modelling framework provides disaggregated estimates of direct and cross attribute elasticities. To ensure that the elasticity outputs are behaviourally meaningful in real markets, it is necessary to calibrate the estimated model by reweighting the mode-specific constants by a known ratio of the sample modal shares to the population modal shares. Without such calibration, the elasticities might be brought into question (see Hensher *et al.* 2005 for more details).

The SC experiment offers a maximum of seven possible alternative modes for metropolitan trips. These alternatives are taxi, hire car[3], car, bus, tram, train, and walk. Any one respondent however is limited to choosing amongst a maximum of three alternatives (with a minimum of two), decided from the initial pre-survey interviews of a small number of travellers[4]. At the commencement of the survey, respondents are asked about a recent trip that they took in which either a taxi or hire car, or both, were possible means of transport for at least part of the trip (see Figure 1). The number and types of alternatives shown to individual respondents is determined by the responses given to the availability of the various alternatives for a recent trip (Figure 2).

[3] A hire car is a car with a chauffeur. It is not a car that an individual hires from a company such as Avis or Hertz. This was made clear to respondents.

[4] This is equivalent to assuming that individuals first choose the set of relevant alternatives from the universal finite choice set and then conditional of this subset, they chose the most preferred alternative. We, like the majority of studies with variable choice sets, do not model the choice of choice sets from the universal finite set.

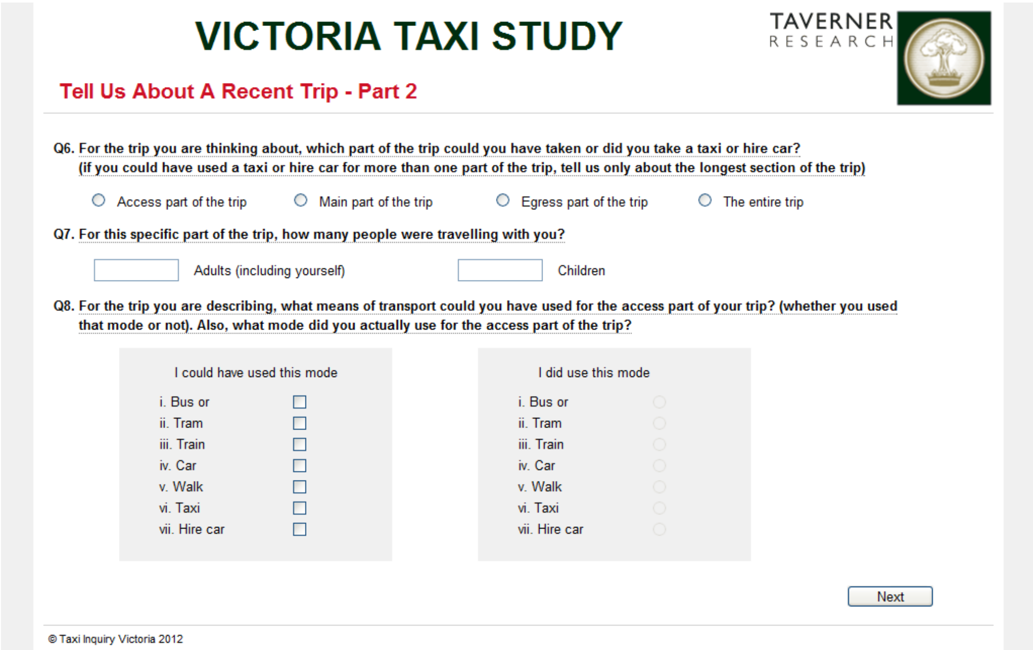

Figure 2: Alternatives available for a recent trip

Where two alternatives were reported as being potential modes for the recent trip (one of which was a taxi and/or hire car and only one of which was actually used for the trip), the SC scenarios were generated to reflect these two modes. Likewise, for a trip in which three modes were available to the respondent to choose from, these three modes were selected to form the alternatives present within the SC scenarios shown to that respondent[5].

Once the alternatives to be shown in the SC scenarios have been determined, the CAPI survey seeks respondent information, either real or perceived, related to the levels of the relevant alternatives or a recent trip that they undertook. The SC experiment then ‘pivots’ the attribute levels of the various alternatives, where a pivot from the reference trip makes sense. As well as the number and types of alternatives varying across respondents, several attributes may vary also. For example, access and egress attributes relate to different mode possibilities. As with the main mode alternatives, these attributes only appear if the respondent indicates that they are a valid option for the trip being examined.

The combinations of levels of each attribute in the SC experiment are designed using NGene, the software developed by Rose, Bliemer, Collins and Hensher. A D-efficient design is used to structure the SC experiment (see Rose and Bliemer 2009 and NGene (http://www.choice-metrics.com)).

Given a lack of prior knowledge as to the precise alternatives faced by a respondent for their specific trip, the SC experiment needed to cater for up to 44 different sets of potential alternative combinations (e.g., taxi versus taxi, taxi versus bus, hire car versus train, taxi versus bus versus tram). Given 44 different potential combinations of alternatives, no single experimental design is possible. As such, it was necessary to build an interface between the survey instrument and NGene whereby the individual specific attribute levels for the recent trip were downloaded in real time to NGene, which generated an individual specific efficient design, which was subsequently fed back to the SC scenarios shown within the survey. This dynamic response process represents the state of art in survey design.

[5] In cases where respondents had more than three alternative modes of transport available to them for the recent trip used to form the context of the SC experiment, the survey instrument selected as one mode either a taxi or hire car as one alternative in the SC experiment, and two of the remaining alternatives from the set as the last two alternatives in the SC scenario.

A pilot study tested the logistical aspects implemented for the main field phase of the project, as well to test the operational capabilities of the CAPI software. Results from the pilot were used to provide priors for constructing the design in the main field phase. An Example choice scenario screen from the final CAPI is shown in Figure 3.

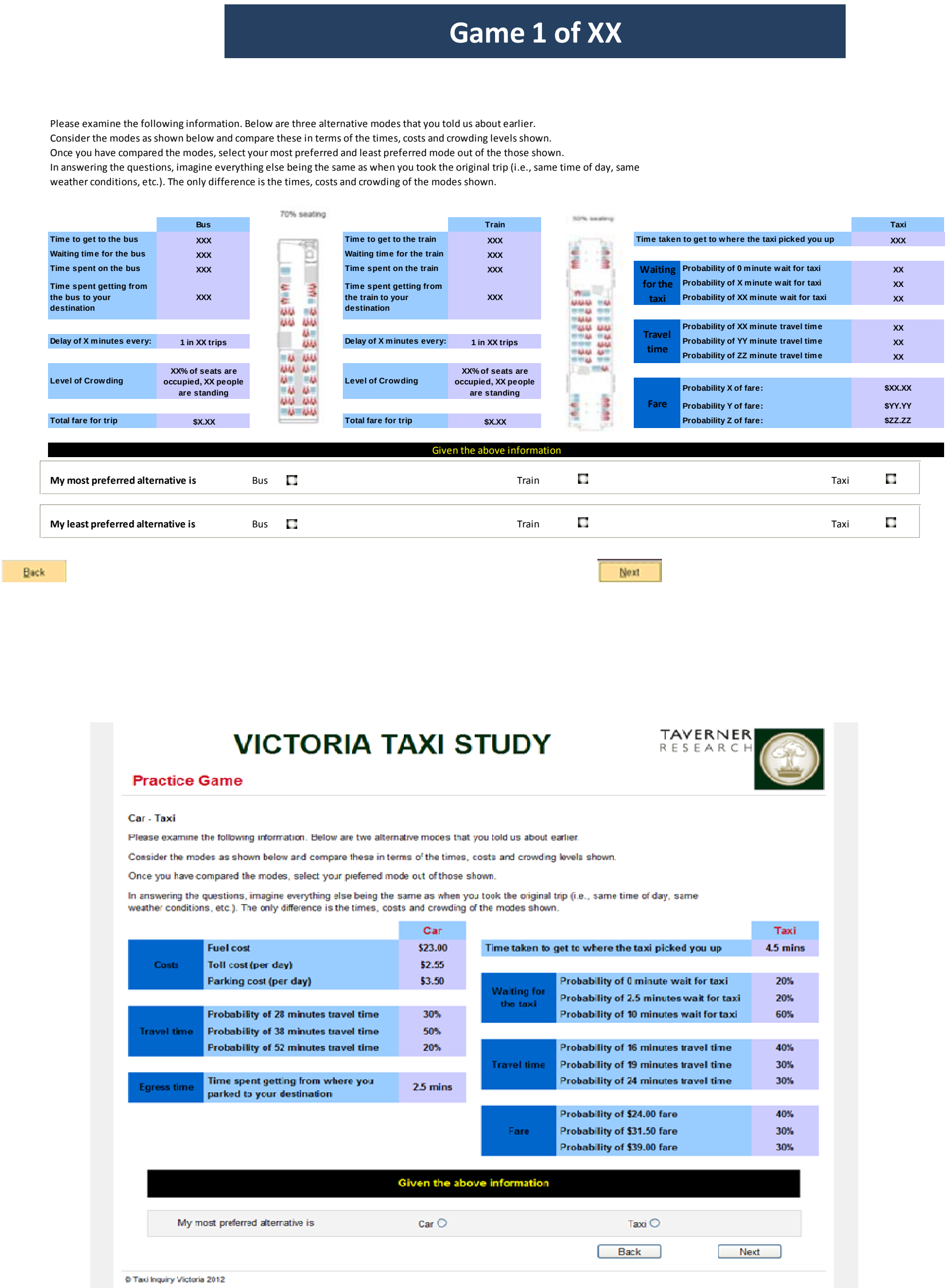

Figure 3:v Examples of mode choice scenario screen

4. The modelling approach

The data obtained from the stated choice study is used in a mixed multinomial logit (MMNL) model to obtain parameter estimates used in the derivation of estimates of elasticities. In this section we provide a brief overview of the MMNL model together with the elasticity formulae. Full details are given in Train (2003) and Hensher *et al.* (2005).

Assume that a sampled individual q (q=1,…,Q) faces a choice among J modes in each of T choice situations. Individual q is assumed to consider the full set of offered alternatives in choice situation t and to choose the alternative with the highest utility. The utility associated with each alternative j as evaluated by each individual q in choice situation t, is represented in a discrete choice model by a utility expression of the general form in (1).

$$U_{qtj} = \boldsymbol{\beta}'_q \mathbf{x}_{qtj} + \varepsilon_{qtj} . \tag{1}$$

$\mathbf{x}_{qtj}$ is the full vector of explanatory variables, including attributes of the alternatives, characteristics of the individual and descriptors of the decision context in choice situation t. The components $\boldsymbol{\beta}_q$ and ε_{qtj} are not observed by the analyst and are treated as stochastic influences. Individual firm heterogeneity is introduced into the utility function through $\boldsymbol{\beta}_q$. Thus,

$$\boldsymbol{\beta}_q = \boldsymbol{\beta} + \boldsymbol{\eta}_q, \tag{2}$$

or $\beta_{qk} = \beta_k + \eta_{qk}$ where β_{qk} is the random coefficient associated with k=1,…,K attributes whose distribution over individuals depends in general on underlying parameters, and $\boldsymbol{\eta}_q$ denotes a vector of K random components in the set of utility functions in addition to the J random elements in $\boldsymbol{\varepsilon}_{qtj}$.

The *MMNL* class of models assumes a general distribution for β_{qk} and an IID extreme value type 1 distribution for ε_{jtq}. Denote the marginal joint density of $[\beta_{q1},\beta_{q2},\ldots,\beta_{qK}]$ by $f(\boldsymbol{\beta}_q|\boldsymbol{\Omega})$ where the elements of $\boldsymbol{\Omega}$ are the underlying structural parameters of the distribution of $\boldsymbol{\beta}_q$, $(\boldsymbol{\beta},\boldsymbol{\Gamma})$. For a given value of $\boldsymbol{\beta}_q$, the *conditional* probability for choice j in choice situation t is multinomial logit, since the remaining error term is IID extreme value:

$$P_{qtj}(\boldsymbol{\beta}_q|\mathbf{X}_{qtj}) = \exp(\boldsymbol{\beta}_q'\mathbf{x}_{qtj}) / \Sigma_j\exp(\boldsymbol{\beta}_q'\mathbf{x}_{qtj}). \tag{3}$$

The *unconditional* choice probability (4) is the expected value of the logit probability over all the possible values of $\boldsymbol{\beta}_q$, that is, it is integrated over these values, weighted by the density of $\boldsymbol{\beta}_q$.

$$P_{qtj}(\mathbf{X}_{qtj},\boldsymbol{\Omega}) = \int_{\boldsymbol{\beta}_q} P_{qtj}(\boldsymbol{\beta}_q \mid \mathbf{X}_{qtj}) f(\boldsymbol{\beta}_q \mid \boldsymbol{\Omega}) d\boldsymbol{\beta}_q . \tag{4}$$

The log likelihood function for estimation of the structural parameters is built up from these unconditional probabilities and can be approximated by simulation. The simulated log likelihood function is:

$$\log L_S = \sum_{q=1}^{Q} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j}^{J} P_{qtj}^{Y_{qtj}} (\boldsymbol{\beta}_{rq} \mid \mathbf{X}_{qtj}) f(\boldsymbol{\beta}_q \mid \boldsymbol{\Omega}), \tag{5}$$

where R is the number of draws in the simulation and Y_{qtj} is an indicator variable equal to 1 if respondent q was observed to choose alternative j in choice situation t, or 0 otherwise. The formula for calculating the mean elasticities is given in equation (6).

$$E\left[\frac{\partial \log P_{qtj}}{\partial \log x_{qtjk,l}}\right] = \frac{1}{Q}\sum_{q=1}^{Q}\int_{\boldsymbol{\beta}_q}[\delta_{j,l} - P_{qtj,l}(\boldsymbol{\beta}_q,\mathbf{X}_{lq})]\beta_{qk}x_{qtjk,l}d\boldsymbol{\beta}_q , \tag{6}$$

where j and l index alternatives, such that $\delta_{j,l} = 1$ if $j \neq l$ or 0 otherwise, x indexes the k^{th} attribute and q indicates the individual. Using R simulated draws from the distribution of $\boldsymbol{\beta}_q$, we obtain the simulated values of the means of the elasticities:

$$E\left[\frac{\partial \log P_{qtj}}{\partial \log x_{qtjk,l}}\right]=\frac{1}{Q}\sum\nolimits_{q=1}^{Q}\frac{1}{R}\sum\nolimits_{r=1}^{R}[\delta_{j,l}-P_{qtj,l}(\boldsymbol{\beta}_{q,r},\mathbf{X}_{lq})]\beta_{qk,r}x_{qtjk,l} \tag{7}$$

5. Sample design and size

Whilst the theory of sampling, as related to discrete choice models, is well developed for revealed preference (RP) data (see Louviere et al. 2000), until recently, little was known about sample size requirements for SC data. Experience suggests however that theory is often discarded for more practical considerations such as issues related to budget and time. Hensher et al. (2005) report that in the experience of many, the minimum sample size requirement for discrete choice experiments is 50 respondents per alternative modelled. Given that each respondent in an SC experiment undertakes multiple choices over a variety of choice sets, each sampled respondent in reality provides multiple data observations. More recently, Rose and Bliemer (2013) have developed specific theory to calculate precise sample size requirements for SC experiments.

Based on theories of optimal experimental design, it is possible to calculate the expected minimum required sample size for a stated choice experiment (Rose and Bliemer 2013). Experimental design theory calculates the expected AVC matrix $\boldsymbol{\Omega}_N$ for a given design which is calculated as the negative inverse of the Fisher information matrix, I_N, which in turn is computed as the second derivatives of the log-likelihood function of the discrete choice model to be estimated. For a given design, $\boldsymbol{\Omega}_N$ can be computed under assumptions about the parameter estimates, where the $\boldsymbol{\Omega}_N$ can be computed for any sample size N. Mathematically, Rose and Bliemer (2013) argue that $I_N = N \cdot I_1$, and hence $\Omega_N = \left(I_N^{-1}\right) = \frac{1}{N}I_N^{-1} = \frac{1}{N}\Omega_1$. Given such a relationship, it follows that the standard error for the k[th] attribute of a design may be represented as

$$se_{kN} = \frac{se_k}{\sqrt{N}}, \tag{8}$$

and the asymptotic *t*-ratio

$$t_k = \frac{\beta_k}{\left(se_k \big/ \sqrt{N}\right)}. \tag{9}$$

Re-arranging Equation (10), we obtain

$$N = \left(\frac{se_k . t_k}{\beta_k}\right)^2, \tag{10}$$

an equation that may be used to compute the theoretical minimum sample size for each parameter of the design.

In generating a design however, the values of β_k are not estimated but rather are assumed inputs in the form of the parameter priors. Similarly, the values of t_k are not estimated, but must be pre-specified by the analyst, with a logical value being 1.96 or greater to ensure that the parameter will be statistically significant with at least 95 percent certainty. In taking this approach, each parameter of the design will have a different theoretical minimum sample size with the theoretical minimum sample size for the overall design being the value of the largest calculated N, thus ensuring that all parameters of the design are likely to be found statistically significant. Note that the sample sizes calculated in this manner represent a theoretical reference as other factors, such as parameter stability may require larger (or smaller) sample sizes than suggested by Equation (10) (see Bliemer and Rose 2011).

The theory of sample size calculations outlined above, whilst dependent on the design and parameter estimates, is far more critical for studies involving smaller samples than for studies involving larger samples. This is because optimal experimental design methods are designed to locate designs which will yield the smallest standard errors possible, which means that smaller sample sizes are generally necessary to obtain the same level of statistical significance for a given population parameter. As such, given the scale of the proposed study, we employed a combination of sampling theories. Firstly, we applied more traditional sampling approaches based on market segmentation, and combined these with the methods developed by Rose and Bliemer (2013) which were applied to each segment. This approach ensures not only robust estimates for forecasting, but the ability to generalise the results to the wider population. Specifically, we segmented the market along geographical lines combined with a choice based sampling approach.

For the current study, we use a quota based sampling. The use of quota based sampling allows for robust parameter estimates across all segments given that respondents of all types are represented in the data.

6. Empirical data

The main field survey was undertaken in 2012, sampling travellers in the Melbourne Metropolitan area. A total of 463 effective interviews were undertaken (see Table 3), representing 5,556 choice observations for model estimation (i.e., 463×12 treatments). The MPTP is a multi-purpose taxi program card, which provide for a 50 percent discount on taxi fares for eligible people.[6]

Table 3: Final sample sizes by segments

	Tourism Segment	Day to Day Activity Segment	*(Combined Tourist and day to day activities segments)*	Business Segment	Night Time Travel Segment	MPTP Card Holder Segment	**Total Sample Size**
Collected	71	117	*(188)*	135	135	39	**497**
Effective interviews	65	112	*(177)*	128	119	39	**463**

6.1 Socio-demographic descriptive statistics by segment

Descriptive statistics are presented in Table 4. Overall, the average age of respondents for the general day to day activity and night time travel segments were 10 years lower than the tourist and business travel segments and 20 years younger than the average age of the MPTP card holder segment. As is to be expected, the average income of the business segment was the highest of all of the segments and the MPTP card holder segment the lowest. The business segment was skewed towards males whilst the MPTP card holder segment had a larger proportion of females. The remaining segments were almost evenly split between male and female.

[6] MPTP gives members half price taxi fares, paying up to $60 per trip. Some members have a yearly limit. The cards cost $16.50 and are valid for six years. An individual can become an MPTP member if they live in Victoria, have a severe and permanent disability, and have a disability that means they cannot use public transport by themself. See http://www.taxi.vic.gov.au/passengers/mptp.

Table 4: Descriptive statistics of socio-demographic characteristics of final sample [7]

	Tourist Segment	Day to Day Travel Activity Segment	Business Segment	Night time travel Segment	MPTP card holder segment
General information					
Age (years)	42.4	33.95	43.53	34.99	55.59
Income ($000 per annum)	48.48	52.2	114.9	48.02	26.67
Gender (1 = female)	58.46%	42.86%	23.44%	45.38%	74.36%
Has a drivers licence	92.31%	90.18%	90.63%	80.67%	56.41%
Employment					
Full Time	35.38%	58.04%	93.75%	44.54%	12.82%
Part Time	18.46%	9.82%	3.13%	22.69%	10.26%
Casual	12.31%	14.29%	3.13%	15.97%	7.69%
Not Employed	33.85%	17.86%	0.00%	16.81%	69.23%

6.2 Modal travel time and cost descriptive statistics by segment

Table 5 provides descriptive statistics for the modal splits and travel times and costs broken down by travel segment. Across all data segments, respondents reported having only one or two modes available to them for the specific recent trip used to generate the SC experiment.

With the exception of the MPTP card holder segment, the average time taken to access a taxi was less than for all other modes, however the average reported waiting time (i.e., time spent at a taxi rank, bus stop or station, or after the time a taxi was booked) for each travel segment was longer for taxi than for any other mode of transport. The average taxi trip was reported as being similar to other main mode vehicle times for all segments. Again, as is to be expected, the fares for taxi are on average substantially larger than for all other modes (except for hire cars)

[7] We could not source any data at a segment level for the population socio-economics, despite extensive efforts.

Table 5: Descriptive statistics of travel characteristics of final sample

	Tourist Segment	Day to Day Travel Activity Segment	Business Segment	Night time travel Segment	MPTP card holder segment
Number of alternatives present in recent trip					
1 or 2 Alternatives	56	101	122	111	35
3 + Alternatives	9	11	6	8	4
Number of times an alternative was available[8]					
Bus	26	11	38	6	3
Tram	9	12	7	25	2
Train	6	13	2	16	6
Car	18	54	45	35	9
Walk	6	12	5	18	0
Taxi	73	131	140	143	60
Hire Car	1	2	25	3	2
Total	**139**	**235**	**262**	**246**	**82**
Model Specific Travel Times and Costs					
Access Times (mins)					
Bus	6.14	6.55	5.94	5.11	2.7
Tram	4.45	1.89	4.92	3.87	1.89
Train	9.04	17.52	10.6	6.83	17.52
Taxi	2.09	2.05	2.28	3.13	4.84
Hire Car	2.03	1.87	2.78	0.91	20.69
Waiting Times (mins)					
Bus	4.72	4.58	4.68	4.58	6.27
Tram	4.64	4.64	4.88	6	4.41
Train	4.61	4.84	5.15	4.62	9.61
Taxi	7.58	7.56	7.53	7.63	7.55
Hire Car	7.52	7.54	7.85	7.43	7.3
Main Mode Travel Times (mins)					
Bus	30.87	35.37	30.46	19.89	86.56
Tram	16.47	31.34	28.47	21.91	37.63
Train	27.95	31.63	28.09	26.4	27.16
Car	34.45	37.51	36.42	28.77	34.28
Walk	31.51	14.97	31.06	27.22	-
Taxi	27.65	35.82	29.84	22.1	31.19
Hire Car	35.64	38.74	40.95	30.93	50.44
Egress Travel Times (mins)					
Bus	4.56	4.75	5.72	8.1	20.93
Tram	2.42	7	4.98	6.07	11
Train	6.47	5.04	6.91	7.95	4.34
Car	2.53	2.86	2.6	1.94	5.88
Trip Specific Costs ($)					
Bus (fare)	$15.65	$14.75	$10.14	$8.80	$11.23
Tram (fare)	$4.60	$3.44	$3.81	$3.51	$2.39
Train (fare)	$6.45	$5.88	$4.38	$5.34	$3.29
Taxi (fare)	$43.62	$51.35	$40.40	$30.13	$23.25
Hire Car (fare)	$62.56	$69.38	$65.00	$52.83	$70.94
Car (petrol costs)	$2.74	$2.96	$2.78	$2.28	$1.57
Car (toll costs)	$3.58	$3.82	$3.03	$2.37	$2.17
Car (parking costs)	$2.58	$16.02	$12.21	$21.20	$21.20

[8] Table 5 is a count of how many times a mode is mentioned in a choice set, whereas Table 3 is the number of respondents in the market segment. For example the 65 effective tourist segment interviews (Table 3) represent 139 modal alternatives based on some individuals having a choice set of two alternatives and others have a choice set of three alternatives.

7. Study results

The main outputs are a set of estimated utility expressions for each market segment used to obtain elasticities related to each user segments preferences for specific service and costs levels. Table 6 presents the results for five econometric models; one MNL model for the MPTP market segment[9] and four MMNL models estimated for the other market segments. Significantly different utility expressions were found to represent the best representation of preference structures of those belonging to each of the travel segments. The MMNL models have several parameters randomly distributed across the population. In estimating the models, each random parameter is specified using a constrained triangular distribution[10]. To estimate the models and the random parameters, Simulated Maximum Likelihood is used with 1,000 Halton draws. A number of specifications were tested for each attribute, including taking logs, squaring the attribute and estimating interaction effects with other attributes and socio-demographic variables. We discuss some of the most interesting findings for a few of the segments.

Overall, the final models provided an excellent model fit with an adjusted ρ^2 value varying from 0.844 (day to day activity) to 0.726 (MPTP). Access time was not found to be statistically significant as a standalone attribute for the tourism and business segments, but was significant for three of the segments. For public transport modes in the tourism segment, however, the attribute was found to have a statistically significant interaction with income, suggesting that higher income earners have a greater marginal disutility as access time increases. For the taxi and hire car modes, access time was not found to be statistically significant, even after testing for several possible interaction effects, except for the MPTP segment.

Waiting time in the current context represents time spent either waiting at a bus stop or train or tram station, or time spent waiting for a taxi or hire car after arriving at a taxi rank or street where a taxi can be caught, or time waiting for a taxi or hire car after the time it was due to arrive if booked. As such, for taxi or hire car, this attribute may act as a proxy for frequency of available services or tardiness on behalf of a taxi or hire car company. In all segments, the best model fit was obtained when the waiting time parameter for the public transport modes was generic, with a separate generic waiting time parameter for the taxi and hire car modes. Between segments, however, various transformations such as the square or natural log of waiting time or a linear waiting time was found to produce the best model results. For example, in the tourism segment, we found, for the public transport modes, that the marginal disutility for waiting time increases as a square root function of time, whereas for the taxi and hire car alternatives, each additional minute of waiting time adds the same amount of marginal disutility as the previous and subsequent minutes spent waiting.

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[9] We were unable to obtain statistically significant parameter estimates for random parameter for this segment, due we suspect to the small sample size.

[10] For example, the usual specification in terms of a normal distribution is to define $\beta_{nk} = \beta_k + \eta_k v_n$ where v_n is the random variable. The constrained specification would be $\beta_{nk} = \beta_k + \beta_k v_n$ when the standard deviation equals the mean or $\beta_{nk} = \beta_k + h\beta_k v_n$ when h is the coefficient of variation taking any positive value. We would generally expect h to lie in the 0-1 range since a standard deviation greater than the mean estimate *typically* results in behaviourally unacceptable parameter estimates.

Table 6: Mode choice models for each trip purpose segment*

		Tourism Segment		Business Segment		Day to Day Activity Segment		Night Time Travel Segment		MPTP Card Holder Segment	
	Mode	Par.	(*t*-ratio)	Par.	(*t*-ratio)	Par.	(*t*-ratio)	Par.	(*t*-ratio)	Par.	(*t*-ratio)
Alternative Specific Constants (w.r.t taxi)											
Constant	Bus	7.588	(3.55)	-11.047	(-3.58)	1.146	(0.36)	5.629	(2.78)	-	-
Constant	Tram	10.070	(4.49)	-2.874	(-0.80)	7.420	(3.28)	-0.007	(-0.01)	8.475	(4.74)
Constant	Train	8.655	(3.86)	-6.053	(-1.79)	6.188	(2.83)	1.223	(0.83)	-	-
Constant	Walk	10.056	(2.22)	-	-	8.481	(1.97)	17.414	(4.04)	-	-
Constant	Car	0.440	(0.21)	-	-	-5.380	(-1.08)	9.311	(3.71)	-	-
Constant	Hire car	2.867	(2.07)	-	-	8.341	(2.15)	-	-	-	-
Access Time											
Access Time	All PT	-	-	-	-	-0.228	(-2.05)	-0.018	(-2.93)	-1.026	(-4.04)
ln(Access Time)	Taxi and Hire car	-	-	-	-	-	-	-	-	-0.527	(-1.87)
Waiting Time											
Wait Time^2	All PT	-0.031	(-1.92)	-	-	-0.033	(-1.68)	-	-	-	-
ln(Wait Time)	All PT	-	-	-0.593	(-1.60)	-	-	-1.208	(-1.99)	-	-
Wait Time	Taxi and Hire car	-0.103	(-2.13)	-	-	-0.061	(-1.79)	-	-	-	-
ln(Wait Time)	Taxi and Hire car	-	-	**-0.385**	**(-1.78)**	-	-	**-0.809**	**(-2.99)**	-1.266	(-1.93)
Main Mode Travel Time											
Main Mode Travel Time	All PT	-	-	**-0.087**	**(-2.57)**	**-0.091**	**(-4.03)**	-	-	-	-
log(Main Mode Travel Time)	All PT	**-2.057**	**(-4.54)**	-	-	-	-	-	-	-	-
Main Mode Travel Time	Walk	**-0.301**	**(-2.40)**	-	-	-	-	-	-	-	-
Main Mode Travel Time^2	Walk	-	-	-0.018	(-1.99)	**-2.755**	**(-3.50)**	-	-	-	-
log(Main Mode Travel Time)	Walk	-	-	-	-	-	-	**-7.688**	**(-5.02)**	-	-
log(Main Mode Travel Time)	Car	-	-	**-2.135**	**(-4.91)**	-3.678	(-2.42)	**-4.127**	**(-6.11)**	-	-
Main Mode Travel Time^2	All PT & car	-	-	-	-	-	-	-	-	-0.002	(-3.43)
Main Mode Travel Time^2	Taxi and Hire car	-	-	**-0.0002**	**(-1.94)**	**-0.0015**	**(-3.74)**	-	-	-	-
log(Main Mode Travel Time)	Taxi and Hire car	-	-	**-**	**-**	-	-	-	-	-1.604	(-2.34)
Egress Time											
Egress Time^2	All PT	-	-	-	-	-0.010	(-2.51)	-	-	-	-
Egress Time^2	Car	-	-	-0.022	(-2.17)	-	-	-	-	-	-
Egress Time	All PT and car	-	-	-	-	-	-	-0.214	(-3.70)	-	-
ln(Egress Time)	All PT and car	-	-	-	-	-	-	-	-	-0.884	(-2.10)
Crowding											
Proportion of people sitting	All PT	-2.535	(-2.41)	-3.611	(-3.76)	-2.852	(-2.51)	-	-	-	-
ln(Proportion of people sitting)	All PT	-	-	-	-	-	-	-1.74536	(-3.94)	-	-
Number of people standing	All PT	-	-	-0.044	(-2.26)	-	-	-	-	-	-
Number of people standing^2	All PT	-	-	-	-	-0.0004	(-2.83)	-0.0001	(-2.63)	-	-
Ln(Number of people standing)	Bus	-1.428	(-4.64)	-	-	-	-	-	-	-	-
Ln(Number of people standing)	Tram and Train	-0.461	(-2.23)	-	-	-	-	-	-	-	-

*Values in bold represent random parameters with constrained triangular distributions

Table 6: cont'd

		Tourism Segment		Business Segment		Day to Day Activity Segment		Night Time Travel Segment		MPTPCard Holder Segment	
	Mode	Par.	(*t*-ratio)	Par.	(*t*-ratio)	Par.	(*t*-ratio)	Par.	(*t*-ratio)	Par.	
					Delay						
Average Delay Time (mins)	All PT	-	-	-	-	-	-	-	-	-0.230	(-2.39)
Average Delay Time (mins)^2	All PT	-	-	-	-	-	-	-0.003	(-1.79)	-	-
Frequency of Delay Time	All PT	-	-	-	-	-	-	-	-	-25.396	(-1.82)
					Travel Costs						
Fare^2	All PT	**-0.011**	**(-3.58)**	-	-	-	-	-	-	-	-
ln(Fare)	All PT	-	-	**-2.846**	**(-4.84)**	**-3.394**	**(-5.03)**	-	-	-	-
Cost (Parking + toll + fuel)	Car	**-0.394**	**(-2.01)**	**-1.325**	**(-2.91)**	**-0.140**	**(-5.81)**	**-0.352**	**(-2.46)**	-	-
ln[Cost (Parking + toll + fuel)]	Car	-	-	-	-	-	-	-	-	-3.525	(-2.62)
Fare	Taxi and Hire car	**-0.156**	**(-4.98)**	-	-	-	-	-	-	-	-
Fare^2	Car	-	-	-	-	-	-	**-0.0024**	**(-4.68)**	-0.093	(-3.88)
ln(Fare)	Taxi and Hire car	-	-	**-4.385**	**(-8.33)**	**-3.747**	**(-6.12)**	-	-	-	-
					Time & Cost Interactions						
Access Travel Time × Income	All PT	-0.002	(-1.97)	-	-	-	-	-	-	-	-
Main Mode Travel Time × Income	Car	**-0.001**	**(-2.55)**	-	-	-	-	-	-	-	-
Main Mode Travel Time × Fare^2	All PT	-	-	-	-	-	-	**-0.0001**	**(-4.24)**	-	-
Main Mode Travel Time × Age	All PT	-	-	-	-	-	-	**-0.001**	**(-1.98)**	-	-
Fare × Age	All PT	-	-	-	-	-	-	-	-	-0.019	(-1.91)
Parking costs × Gender (1 = Female)	Car	-	-	-	-	-	-	-	-	0.125	(1.89)
Toll costs × ln(main mode travel time)	Car	-	-	-	-	-3.059	(-6.01)	-	-	-	-
Main Mode Travel Time × Age	Taxi and Hire car	-	-	-	-	-	-	**-0.009**	**(-7.09)**	-	-
Wait Time × Age	Taxi and Hire car	-	-	-	-	-	-	-	-	-0.003	(-1.99)
Main Mode Travel Time × Income	Taxi and Hire car	**-0.0004**	**(-2.26)**	-	-	-0.0002	(-4.00)	-	-	-	-
					Socio-demographics and other variables						
Number of children present during trip	All PT	-	-	-	-	-6.830	(-2.72)	-	-	-	-
Afternoon trip (1 = yes)	All PT	-	-	-	-	-6.971	(-3.37)	-	-	-	-
Trip purpose - visit friends	All PT	-	-	-	-	4.438	(1.88)	-1.464	(-1.97)	-	-
Trip purpose - shopping trip	All PT	-	-	-	-	6.364	(2.27)	-10.208	(-4.84)	-	-
Gender (1 = Female)	All PT	-	-	-	-	-	-	-	-	1.965	(2.06)
Income	Walk	-0.074	(-2.53)	-0.090	(-1.92)	-0.091	(-3.00)	-	-	-	-
Need to arrive on special time (1 = No)	Car	-	-	3.127	(2.88)	-	-	-	-	-	-
Trip purpose - shopping trip	Car	-	-	-	-	-	-	-	-	3.001	(2.71)
Need to arrive on special time (1 = No)	Taxi and Hire car	-	-	-	-	-3.136	(-3.37)	-	-	-	-
Weather (overcast)	Taxi and Hire car	-	-	-	-	-	-	4.276	(3.99)	-	-
Weather (light rain)	Taxi and Hire car	-	-	-	-	-7.909	(-2.58)	7.267	(2.22)	-	-
					Model Fits						
LL(0)		-1621.964		-3194.022		-2794.769		-2969.443		-910.686	
LL(β)		-259.910		-569.172		-428.194		-565.488		-240.618	
ρ^2		0.840		0.822		0.847		0.810		0.736	
Adj. ρ^2		0.836		0.820		0.844		0.806		0.726	
Number of respondents		65		128		112		119		39	
Number of choice observations		780		1536		1344		1428		468	

Similarly for the main mode travel time, various transformations gave the best fit for each of the segments. For example, in the business traveller segment, a generic parameter across a linear in the attribute main mode public transport travel time gave the best model fit whilst for walk, the square of travel time produced the best result. Likewise the square of travel time was used to enter the taxi and hire car utility functions. The log of travel time, however, was found to best represent the influence on utility for the car mode. Unlike the tourist segment, egress for the car mode was found to be statistically significant and negative in the business segment, and hence was retained in the final model.

Crowding in public transport was found to have a statistically significant influence on mode choice in all but the MTPT segment. Two crowding attributes were included in the SC scenarios that respondents were asked to complete; one reflecting the number of seats occupied, and the other representing the number of people standing[11]. For the seating attribute, a generic attribute across all modes in four segments was found to provide the best model fit, with one of the segments (night time travel) having a logarithmic transform. The influence of the number of people standing was specified as generic across all modes in three segments, but alternative-specific to bus in the tourism segment. The negative sign for the proportion of people sitting is explained as follows – if the proportion sitting is higher, the chance of getting a seat is lower and hence the marginal disutility is negative, suggesting that the probability of choosing that mode decreases, ceteris paribus.

A generic parameter estimate was applied to the square of fare for all public transport modes for the tourism segment and the natural log of fare for the business and day to day activity segments; alongside a generic taxi/hire car parameter for a linear in the attributes for tourism or logarithmic treatment of fare in business and day to day activity segments. For car, an aggregation of all car related costs (fuel, parking and toll costs) was used in the final models, after investigating the possibility of different parameter estimates. In all cases, the influence of cost was statistically significant and negative, suggesting as expected that increasing costs will result in lower utility, and hence lower market shares for these modes.

Socioeconomic and other influences varied in their roles between the segments. In the tourism segment, income was found to be statistically significant and negative as a main effect within the walking alternative. This suggests that, all else being equal, higher income earners have a higher marginal disutility for walking and are more likely to select another mode of transport. In the day to day activity segment, for the public transport modes, as the number of children present during the trip increased or if the trip was in the afternoon, this resulted in an increased marginal disutility for using these modes; whereas for trips involving travelling to visit friends or to the shops, a higher marginal utility was obtained. The model results suggest that respondents who did not have a specific requirement to be at their destination at a given time are less inclined to take a taxi relative to those who stated that they had a deadline to meet, while those travelling during light showers (relative to sunny and overcast) were also less likely to take a taxi or hire car than other modes, all else being equal.

Contrary to the general day to day activity segment model, the night time model results suggest that trips involving travelling to friends or to the shops produce a lower marginal utility or generates a marginal disutility for public transport modes relative to other modes, suggesting that such trips undertaken during the day are more likely to result in public transport use, but less likely during the night. Further, opposite to the general day to day activity segment model, light rain or the possibility of rain (i.e., overcast) are more likely to generate a taxi or hire car trip at night than under other weather patterns, all else being equal. Weather is often suggested

[11] The crowding attribute was simplified in contrast to the trip time reliability attribute that has assigned probabilities of occurrence. In future studies we recommend a similar treatment of crowding as specified for reliability.

(anecdotally) as a factor and when it is raining (compared to when it is sunny)[12], people tend to find using a taxi very attractive compared to (at least) using mainstream public transport.

Two covariates were found to be predictors of mode choice for the MPTP card holder segment. Firstly, females were found to prefer the use of public transport relative to males. Secondly, MPTP card holders were more likely to choose the car alternative for trips involving travelling to the shops, relative to other modes, all else being equal. This may be related to the availability of help from others during these activities at the destination.

8. A decision support system

To operationalise the models, a Decision Support System (DSS) was developed to test how changes to attributes associated with the modes will likely affect the market shares, including providing evidence on the implied direct and cross elasticities. The construction and inclusion of a DSS for the current study is necessary for a number of reasons. Firstly, the sampling strategy required for estimating the mode choice models was such that the sample of trips collected and used to generate the SC experiment are not representative of the overall current travel patterns. Based on data on population modal shares, taxi trips represent only 0.42 percent of all trips undertaken in the Melbourne metropolitan area. As such, a random sample of 505 respondents would be expected to yield less than three recent trips undertaken in which a taxi was used, and possibly a not much larger sample of trips where a taxi was considered to be an alternative mode of transport, even when not chosen. We deliberately oversampled the number of taxi trips relative to the general number of trips so as to be able to estimate the models of interest.

The oversampling of certain modes has a number of implications in terms of how the estimated models may be used in practice. Given the impact on mode specific constants[13], it is typical to calibrate the constants after fixing the remaining parameter estimates. After calibrating the modal constants, the mode shares of the model should reflect the known market shares. The process of calibrating the modal constants however requires that the estimated model for each segment in which some parameters have a distribution be fed through the data.

In the current context, however, a number of the sampled trips within the data involved trips where respondents reported being captive to taxi as the only mode available for the trip. Such trips were particularly prevalent for the MPTP card holder market segment. In the SC experiment, these respondents were shown scenarios in which they were asked to choose between two hypothetical taxis. The high number of such trips in the SC data presents problems when aggregating the choice shares as well as when calibrating the modal constants. For modal captive respondents, the probability of selecting a taxi is always one, and hence the proportion of such respondents within a data set represents the minimum mode share that could be obtained for that mode given the data set, independent of any constants or parameter estimates. Not even the imposition of an infinite (or negative infinite) modal constant will produce a lower market share than presented in Table 7, given such a data set.

[12] Although we allowed for the possibility of a recent trip of a heavy downpour, there was very little of this and the majority of respondents indicated it was sunny, overcast or a light rain. We would conjecture that had we a sizeable sample who experienced a downpour on the reported recent trip, we would have identified a statistically significant positive sign for the parameter attached to this attribute level in the context of night travel in particular.

[13] The modal constants are important for a number of reasons, none more so than to obtain elasticity estimates. In discrete choice models, elasticities are a function of not just the parameter estimates and the data, but also the choice probabilities and attribute levels. As such, it is important that the mode specific constants reproduce the known market shares, otherwise any elasticities generated from the model will be biased.

Table 7: Percentage of taxi captive trips by segment

Segment	Proportion of captive respondents
Tourism Segment	9.92%
Business Segment	11.51%
Day to Day Activity Segment	16.17%
Night Time Travel Segment	19.51%
MPTP card holders	51.22%

Given the nature of SC data, and the desire to derive elasticity estimates, it is necessary to calibrate the model constants to reflect the true market shares after applying the model to real market data. Unfortunately, the use of quota based sampling made the revealed preference data collected for the purposes of model estimation in the survey unsuitable for the purposes, and no other source of revealed preference data with all the modes presents was available. Further, the fact that the survey itself required that all respondents had either taxi or hire car present in each choice task, with some respondents only having these modes(and hence no other modes deemed suitable), meant that model calibration was not possible. As such, we simulated synthetic respondents to match the known travel time and cost distributions for all modes and used this data to first calibrate the models, and estimate the elasticities.

In the current paper, we simulated data for each mode for a defined number of respondents, arbitrarily selected as 2,500. In simulating the data, we uses data from the 2011 Metro Network Service Provider (NSP) data set to establish the average taxi travel times (16.04 minutes) and fares ($23.57). For each trip segment we then draw, from a log-normal distribution, taxi travel times with the same mean travel time as that obtained from the 2011 Metro NSP data. Next, fares are drawn for each travel time based on the fare formula currently used in Victoria[14] with a stochastic term to provide some variation. The fare and travel time distributions for the general day to day activity segment are shown in Figure 4. The remaining attribute levels are then drawn from similar distributions for the remaining modes based on the values obtained from the sample, but correlated with the taxi times and costs (so that for example, shorter taxi trips are matched with shorter train trips).

We then calibrated the mode-specific constants using the simulated data based on data obtained from the Victorian Department of Transport to obtain a population-level modal share[15]. Details of the DSS are given in Appendix A.

Table 8 presents some indicative taxi direct elasticities obtained from the DSS. Shown are the elasticities obtained for a two minute increase in the in-vehicle times for all trips irrespective of trip length and a $2.00 fare increase for taxis irrespective of trip length. In brackets are the percentage changes that are generated given the absolute time or fare increases. Also shown are the elasticities for waiting time, main mode or in-vehicle travel time and fares (based on a ten percent changes to waiting time, travel time or fare respectively).

[14] http://www.taxifare.com.au/rates/australia/melbourne/

[15] Details of this process are available on request from the authors.

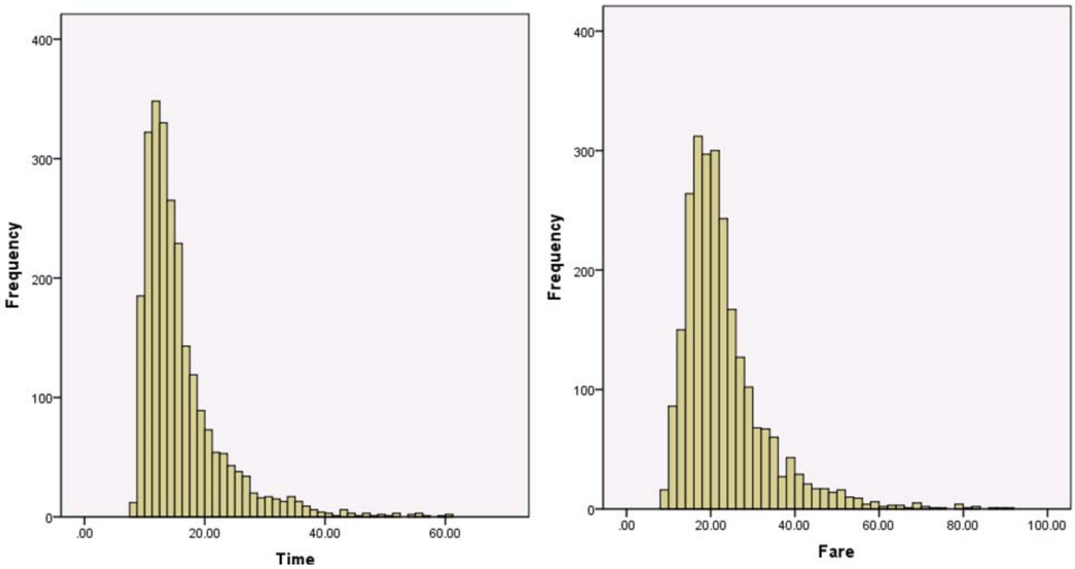

Figure 4: Simulated travel time and fare distributions for the general day to day travel segment

Table 8: Some Indicative taxi elasticities obtained from the DSS

	Tourism Segment	Business Segment	Day to Day Activity Segment	Night Time Travel Segment	MPTP card holder Segment	Weighted Average
Attribute	Absolute change					
In-vehicle time (2 min inc.)	-0.387 (14.03%)	-0.079 (14.10%)	-0.471 (14.08%)	-1.263 (14.03%)	-0.964 (14.10%)	-0.477 (14.06%)
Fare ($2.00 inc.)	-1.437 (9.72%)	-0.556 (9.92%)	-0.671 (9.85%)	-1.079 (9.84%)	-0.578 (19.91%)	-0.977 (9.81%)
Attribute	Percentage change					
Waiting time (10% inc.)	-0.603	-0.226	-0.273	-0.393	-1.533	-0.340
In-vehicle time (10% inc.)	-0.430	-0.123	-0.657	-1.314	-0.954	-0.573
Fare (10% inc.)	-1.478	-0.645	-0.753	-1.132	-0.605	-1.042

It should be noted that there are very few empirical studies available of sufficient quality (see Table 1) to be able to be used as a set of reference taxi elasticities. We might reasonably claim that the current study is behaviourally, the most detailed study ever conducted, including greater market segmentation than previous studies. Furthermore the equations used are highly non-linear in the influencing attributes such as fares and travel times (including logarithmic, quadratic and interaction forms), such that a set of average elasticities within each trip purpose segment are not meaningful. Interpreting the Table 8 elasticities, as expected, the taxi direct elasticities for the business segment are lower than those of the other segments, with the exception of the fare elasticity for the MPTP card holder segment. MPTP card holders receive heavily discounted fares when travelling by taxi. The relatively small travel time elasticity for business travellers is an interesting finding, suggesting that the convenience of taxi use (door to door) is being built into the travel time response, in a context where many business trips are also not paid by the actual taxi user, but by the traveller's employer or client. Tourists and late night travellers have the highest fare elasticities. Given the current exchange rate for the Australian dollar (slightly above parity with the US dollar), the purchasing power for many international tourists has been significantly diminished of late, and hence they are relatively price sensitive with lower disposable income to spend on activities and travel. Those travelling late at night might be expected to have a relatively higher fare elasticity compared to other segments, given that much of the segment includes trips travelling to and from hotels and nightclubs or from other such expensive activities, where extra expenditure on travel might be seen as a significant impost on the night budget. Night time travellers and MPTP card holders appear to be relatively more sensitive to changes in taxi travel time than other segments.

Despite caveats on strict comparability, assessing the elasticities reported in Table 1 relative to the findings in Table 8 (albeit based on specific trip and policy assumptions) provides some confidence that the results from the current study are plausible and consistent with existing (but limited) research evidence. Indeed, all elasticities, with the exception of MPTP card holders (which have not been studied before), fall within the ranges of elasticities found from the literature review. For example, the taxi fare elasticities range from -0.22 to -1.75 with the largest reported value associated with trips associated with "going out". This is similar to our late night travel segment which also has the largest fare elasticity. Furthermore, our waiting time elasticities appear to be in line with those of the reported literature, as is the relative rankings of the elasticities of fare and travel time, followed by waiting time. Indeed, our values are very similar to those reported by Rouwendal (1998).

9. Conclusions

This paper has investigated the behavioural influences on traveller choice of mode for specific trips in the Melbourne metropolitan area, with a special focus on understanding the factors that influence the choice of, and hence demand for, taxi services. Given the importance of positioning preferences for taxi services within the broader set of modal options, we have developed a modal choice model capability for all available modes of transport for trips undertaken by individuals or groups of individuals in the broad categories of corporate travellers, international and domestic tourists, late night social users, locals undertaking social outings, and users that hold multi-purpose taxi program cards, which provide for a 50 percent discount on taxi fares.

New data has been collected using state of art choice experiments referenced around recent modal trip activity of a sample of individuals undertaking travel within the Melbourne Metropolitan Area in 2012. Combined with estimated modal choice models of the multinomial or mixed multinomial logit form, we have identified the key drivers of choices made amongst available modes of transport, with a specific focus on the role that taxis and hire cars play in the modal mix.

The findings for each trip purpose segment, especially in respect of fares and service levels, have been integrated into a Decision Support System, calibrated to known population modal market shares, to provide a capability of identifying behavioural responses to changes in fares and service levels (represented as direct elasticities) as well as predictions of changes in market modal shares. Indicative mean elasticity estimates have been provided as a means of illustrating the types of elasticity outputs and as a basis of comparing them with the limited available evidence.

This study offers a new benchmark for evidence on fare and service elasticities of demand for taxis. To obtain context-specific elasticity estimates, desktop DSS capability, such as developed for this study, is necessary to enable analysts to investigate numerous demand-response scenarios with respect of reform options for the taxi sector. In ongoing research, we are building a joint RP-SP model to establish the role that the RP model plays in identifying scale adjustments for use in rescaling the SP model as a contrast to the calibration undertaken in this paper through the DSS.

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Appendix A: The decision support system

The DSS screens of interest are the Input (Figure A1) and Scenario output screens (see Figure A2). The input screen allows users to enter as either percentage or absolute changes, changes to the attribute levels of the seven modes used as part of this study. For the main in-vehicle or main mode walk times and fares, the DSS has separated the data into trips less than 20 minutes, between 20 and 40 minutes, and greater than 40 minutes. This allows the user to change as an absolute number, the fares or costs for subsets of the data. For example, the user can change the fare only for trips that are under 20 minutes, or increase the travel times for trips over 40 minutes. The DSS also allows for several attributes to be changed at once or only a single attribute to be changed, depending on the specific scenario being tested.

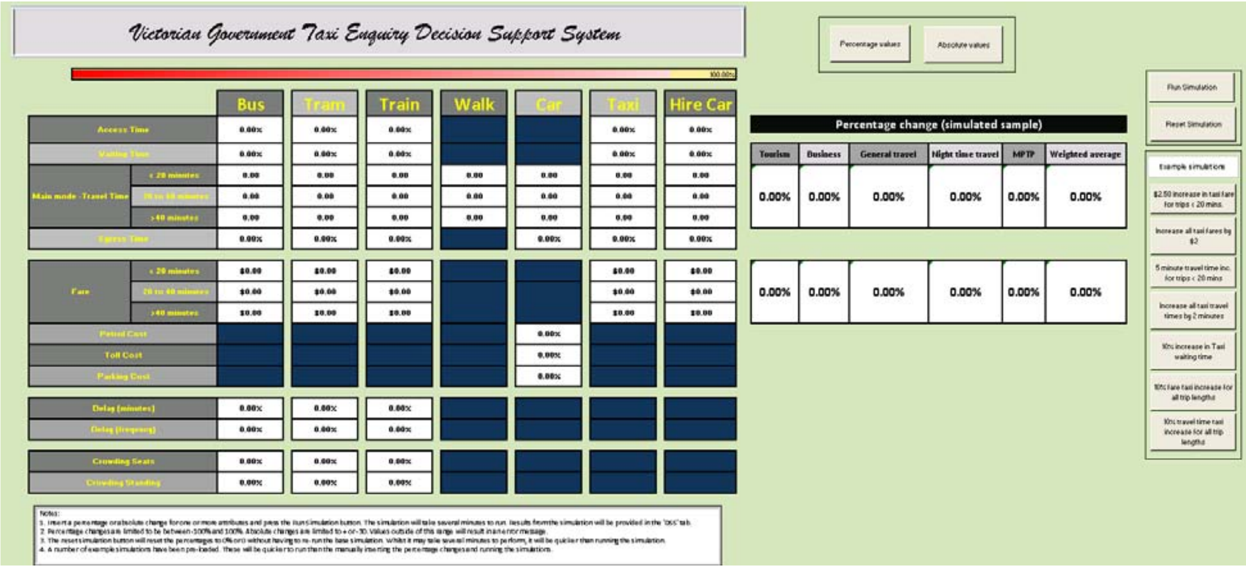

Figure A1: DSS input screen

As shown in Figure A1, to the right of the scenario section where attribute level changes can be made, are the results of calculations that convert for the taxi mode, the absolute changes for main mode times and fares into percentage changes. For example, if the user wishes to impose a $2.50 increase in taxi fares for trips that are less than 20 minutes, the numbers shown in these boxes calculate and show what the percentage change in fares by segment is. Note that the percentage changes will be greater for shorter trips than longer trip lengths, for a given fare change. Two buttons are also available that will switch the main mode or in-vehicle travel times and fares between percentage and absolute value changes.

Not accessible to the user, the DSS makes use of the discrete choice models estimated that are linked to the simulated respondents as discussed above. Given the use of MMNL models for four of the five segments, simulation is required for these models to obtain the predicted market shares. The DSS utilises 1,000 Halton draws per each of the 2,500 respondents to obtain the predicted market shares for a given scenario. As such, each scenario run requires 17,500,000 (2,500 respondents × 1,000 draws × 7 (modes)) calculations per market segment. Given the large number of simulated draws, the running of each scenario is time consuming. Further details of the DSS are available on request.

Victorian Government Taxi Enquiry Decision Support System

Tourism Segment

	Bus	Tram	Train	Walk	Car	Taxi	Hire Car
Base market share	0.917%	0.781%	1.118%	12.508%	84.520%	0.146%	0.010%
Total people	51900	44200	63300	708200	4785500	8282	567
Scenario market share	0.917%	0.781%	1.118%	12.508%	84.520%	0.146%	0.010%
Total people	51900	44200	63300	708200	4785500	8282	567
Change in Market Share	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%

Business Segment

	Bus	Tram	Train	Walk	Car	Taxi	Hire Car
Base market share	0.884%	3.163%	9.802%	6.097%	79.436%	0.538%	0.080%
Total people	21700	77600	240500	149600	1949100	13206	1963
Scenario market share	0.884%	3.163%	9.802%	6.097%	79.436%	0.538%	0.080%
Total people	21700	77600	240500	149600	1949100	13206	1963
Change in Market Share	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%

Day to Day Activity Segment

	Bus	Tram	Train	Walk	Car	Taxi	Hire Car
Base market share	1.459%	1.318%	2.508%	13.173%	81.213%	0.278%	0.050%
Total people	84225	76125	144825	760575	4688925	16075	2887
Scenario market share	1.459%	1.318%	2.508%	13.173%	81.213%	0.278%	0.050%
Total people	84225	76125	144825	760575	4688925	16075	2887
Change in Market Share	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%

Figure A2: DSS output screen I