Establishing Fare Elasticity Regimes for Urban Passenger Transport: Time-Based Fares for Concession and Non-Concession Markets Segmented by Trip Length

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ABSTRACT

A missing element in public transport patronage prediction is often a matrix of direct and cross fare elasticities for specific fare classes. This paper employs a combined stated preference and revealed preference data set to obtain this type of matrix, reflecting the market environment for concession and non-concession travelers using public transport for short and long trips. A heteroskedastic extreme value choice model relaxes the constant variance assumption of the multinomial logit model so that empirically realistic cross elasticities can be obtained. The elasticities obtained from the study indicate the level of switching between ticket types and between the car and bus modes for any given change in fare levels or types.

INTRODUCTION

Public transport operators increasingly use yield management techniques in establishing mixtures of ticket types and fare levels. In predicting the response of the market to specific fare classes, a knowledge of how various market segments respond to both the choice of ticket type within a

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public transport mode and the choice between modes is crucial to the outcome. In some circumstances, the interest is in evaluating the patronage and revenue implications of variations in offered prices for the existing regime of fare classes; in other circumstances, the interest is in changes in the fare class offerings either through deletions and/or additions of classes.

A missing ingredient in many operational studies is a matrix of appropriate direct and cross fare elasticities that relates to specific fare classes within a choice set of fare class opportunities. Surprisingly, the research literature is relatively barren of empirical evidence that is rich enough to distinguish sensitivities to particular fare class offerings within a predefined choice set of offerings. Although there is a plethora of empirical evidence offered on direct elasticities (Oum et al 1992; Goodwin 1992), primarily treated as unweighted or weighted average fares within each public transport mode, there is limited evidence on cross elasticities (see Hensher (Forthcoming) for a brief review of the literature). Elasticities related to specific ticket types are generally absent from the literature, and non-existent in Australia.

This article departs from the reliance on average fares, distinguishing between fare classes for bus travel for concessionary and non-concessionary travel in the Newcastle metropolitan area (approximately 160 kilometers north of Sydney). Non-concessionary travel refers to all discounted travel, excepting pensioners who are excluded from this study. Full matrices of direct and cross share elasticities are derived for two future scenarios: Scenario I where the current Single and TravelPass/TravelTen tickets are eliminated and replaced with four timed tickets: one-hour, four-hour, one-day, and weekly tickets; and Scenario II where the four timed tickets are introduced with the retention of the current single fare. A TravelTen ticket entitles the user to 10 one-way trips over an agreed number of sections; a TravelPass entitles the purchaser to an unlimited number of one-way trips over a seven-day period over sections identified by the color coded ticket purchased. The only other major mode in the Newcastle area is the car. Taxis and trains (long distance) are excluded since they compete very little with the bus system, the major modal focus of this study.

To evaluate sizeable variations in the levels of fares in each ticket class so that operators have extended policy intelligence beyond market experience, stated choice responses are combined with a knowledge of current modal attributes from revealed preference data to assess the ticket and mode choices made.

The motivation for such disaggregation is twofold. First, public transport operators have little interest in empirical approaches that treat all fare classes as an equivalent one-way average fare—this is not a useful operational framework within which to make decisions on fare setting. Secondly, empirical measurement of indicators of behavioral response to specific ticket types, given the set of ticket types available, will enable bus operators to identify the impact of these various ticket type (and level) scenarios on overall patronage and revenue. The incorporation of these elasticities into a Decision Support System (DSS) allows an operator to evaluate the implications of various fare policies on patronage, revenue, market share, and the net social benefit per dollar of "subsidy" or community service obligation (CSO) payment provided.

The paper is organized as follows. The next section introduces a discrete choice model associated with the family of random utility models—heteroskedastic extreme value logit (HEVL)—which relaxes the strong assumption of constant variance in the unobserved effects to allow the cross elasticities to break away from the equality constraint imposed in the multinomial logit model and within partitions of the popular nested logit model. The following section outlines the empirical context in which we source revealed and stated preference data to provide an enriched utility space for assessing behavioral responses to fare scenarios extending beyond the range observed in real markets. The next section presents the empirical evidence, including a full matrix of direct and cross share elasticities for concession and non-concession travel over short and long distances. A set of conclusions highlights the major contribution of this study.

SPECIFYING A CHOICE MODEL

The ticket type and mode choice model is based on the utility maximization hypothesis, which assumes that an individual's choice of ticket type is conditional on mode. The individual's choice of mode is a reflection of the preferences for each of the available alternatives, and the alternative with the highest utility is selected. The utility that an individual associates with an alternative is specified as the sum of a deterministic component (which depends on observed attributes of the alternative and the individual) and a random component (which represents the effects of unobserved attributes of the individual and unobserved characteristics of the alternative).

In the majority of mode choice models, the random components of the utilities of the different alternatives are assumed to be independent and identically distributed (IID) with a type I extreme value distribution. This results in the multinomial logit (MNL) model of mode choice (McFadden 1981). The multinomial logit model has a simple and elegant closed-form mathematical structure, making it easy to estimate and interpret. However, it is saddled with the "independence of irrelevant alternatives" (IIA) property at the individual level (Hensher and Johnson 1981; Ben-Akiva and Lerman 1985); that is, the MNL model imposes the restriction of equal cross elasticities due to a change in an attribute affecting only the utility of an alternative i for all alternatives $j \neq i$. This property of equal proportionate change is unlikely to represent actual choice behavior in many situations. Such misrepresentation of choice behavior can lead to misleading projections of mode share on a new or upgraded service and of diversion from existing modes. The nested logit model is a variant of the MNL model, relaxing the constant variance assumption between branches while preserving it within a branch of the nested structure (McFadden 1981; Hensher 1991).

The model developed herein assumes independent, but non-identical random terms distributed with a type I extreme value distribution. Unequal variances of the random components are likely to occur when the variance of an unobserved variable that affects choice is different for different alternatives. For example, in a mode choice model, if comfort is an unobserved variable whose values vary considerably for the bus mode (based on, say, the degree of crowding on different bus routes) but little for the automobile, then the random components for the automobile and bus will have different variances (Horowitz 1981). We apply this model in the current study. Once we relax the constant variance assumption, we have to distinguish scale and taste, to which we now turn.

The Inseparability of Taste and Scale

It has been well known for some time that a fundamental link exists between the scale of the estimated parameters and the magnitude of the random component in all choice models based on Random Utility Theory (RUT, see McFadden 1981). Let

$$U_{iq} = V_{iq} + \epsilon_{iq}, \tag{1}$$

where U_{iq} is the unobserved, latent utility individual q associates with alternative i; V_{iq} is the systematic, quantifiable proportion of utility that can be expressed in terms of observables of alternatives and consumers; and the ϵ_{iq}'s are the random or unobservable effects associated with the utility of alternative i and individual q. All RUT-based choice models are derived by making some assumptions about the distribution of the random effects; regardless of the particular assumption adopted, there is an embedded scale parameter, which is inversely related to the magnitude of the random component that cannot be separately identified from the taste parameters.

For example, to derive the MNL choice model from (1), we assume that the ϵ_{iq}'s are IID Type I Extreme Value (or Gumbel) distributed. The scale parameter $\lambda \geqslant 0$ of the Gumbel distribution is inversely proportional to the standard deviation of the error component, thus,

$$\sigma^2_{iq} = \pi^2 / 6\lambda^2.$$

The identification problem of RUT-based choice models shows itself in the MNL model through the fact that the vector of parameters actually estimated from any given source of RUT-conformable preference data is $(\lambda\beta)$, where β is the vector of taste parameters. This is seen in the full expression of the MNL choice probability:

$$P_{iq} = \frac{\exp(\lambda V_{iq})}{\sum_{j\epsilon C_n} \exp(\lambda V_{jq})} = \frac{\exp(\lambda\beta X_{iq})}{\sum_{j\epsilon C_q} \exp(\lambda\beta X_{jq})}, \quad (2)$$

where P_{iq} is the choice probability of alternative i for individual q, and the systematic utility V_{iq} = βX_{iq}. Since a given set of data is characterized by some value of λ, this constant is normalized to some value (say, 1), and analysis proceeds as if ($\lambda\beta$) were the taste parameters.

The reason for the pervasiveness of the identification problem is that choice models are specifying a structural relationship between a categorical response and a latent variable (i.e., utility). As in structural equation models involving latent variables, it is necessary to specify both origin *and* variance (read "scale") for the latent variable(s) to permit identification of utility function parameters (Hensher et al Forthcoming).

Recognition of the role of the scale parameter in the estimation and interpretation of choice models came somewhat late in the game, but was triggered by the desire to combine sources of preference data, especially revealed preference (RP) and stated preference (SP) data. Morikawa (1989) noted that the fundamental identification problem was confined to a single preference data source, and that the ratio of λ's in two or more sources of data could be identified.

The estimation problem amounts to placing an equality restriction on the taste parameters of K preference data sources to be combined (i.e., β_1 = … = β_K = β) and estimating K additional scale parameters (β_1,…, β_K). One of these scale parameters must be fixed, say λ_1 = 1. The remaining scale parameters are then interpreted as inverse variance ratios with respect to the referent data source. The corresponding unrestricted model frees the taste parameters and the scale factors for the K data sources by estimating ($\lambda_k\beta_k$), k = 1,…,K. The null hypothesis of interest is that of taste invariance across data sources, after permitting variance/reliability differences such an hypothesis can be tested using a likelihood ratio statistic.

The existing studies with the exception of Hensher (Forthcoming) using data from multiple sources have all adopted a constant variance assumption within the set of alternatives associated with each data set. They have set the scale parameter to 1.0 for one data set and rescaled the other data set by a scale parameter that is constant (but possibly not equal to 1.0) across the set of alternatives. The cross elasticities remain subject to the IID assumption and hence are potentially ill conditioned. We relax the constant variance assumption and allow all scale parameters to differ within and between two data sets. We do this by a procedure known as a heteroskedastic extreme value (HEV) random utility model (Bhat 1995). Joint estimation is essential to enable direct comparability in rescaling between the RP and SP choice models, since only one alternative across both data sets has its variance on the unobserved effects arbitrarily set to 1.0.

Random Effects Heteroskedastic Extreme Value Model

Allenby and Ginter (1995), Bhat (1995), and Hensher (In press) have implemented the HEV model on a single data source. Hensher (Forthcoming) has applied the HEV model to joint estimation of SP and RP data. The indirect utility function (1) is defined as:

$$U_{iq} = \lambda_{iq}\alpha + \lambda_{iq}\beta X_{iq} + \epsilon_{iq.} \quad (3)$$

The MNL model assumes IID, that is, $\lambda_i = \lambda_j \ \forall\ j \epsilon J$, i ≠ j, and $\epsilon_{iq} = \epsilon_{jq} = \epsilon$. Now assume that the λ_{iq} are equal to λ_l for all individuals q; in addition, assume they are independently, but not identically, distributed across alternatives according to the Type I Extreme Value density function

$$f(t) = \exp(-t)*\exp(-\exp(-t)) = -F(t)*\log(F(t)),$$

where F(.) is the corresponding cumulative distribution function. If the decision rule is maximal utility, then the choice probabilities are given by

$$P_{iq} = \int_{-\infty}^{\infty} \prod_{j \neq i} F(\lambda_j)[V_{iq} - V_{jq} + \epsilon_{iq}]\lambda_i f(\lambda_i \epsilon_{iq}) d\epsilon_{iq}. \quad (4)$$

The probabilities are evaluated numerically, as there is no closed-form solution for this single dimensional integral. The integral can be approximated, for example, using Gauss-Laguerre quadrature (Press et al 1986). Computational experience has shown that a 68-point approximation is sufficient to reproduce taste parameter estimates (see Greene 1996). Selecting appropriate starting values is critical to the search for an optimal solution since, unlike MNL, there is no unique optimum log-likelihood at convergence; local optima exist as well as the global optimum. Experience suggests that MNL starting values are highly recommended.

The heteroskedastic extreme value model nests the restrictive MNL and is flexible enough to allow differential cross elasticities among all pairs of alternatives. It avoids the *a priori* identification of mutually exclusive market partitions of a nested MNL structure, and is thus preferable to the nested MNL model in which cross elasticities are behaviorally meaningful between alternatives within a branch of a nest but not between branches. The MNL model is of no interest here since it cannot reveal the cross elasticities that are required to establish the extent to which travelers may switch between fare classes within a mode and between modes. In contrast, the nested MNL model may be of value provided one can identify the best tree structure, consistent with global utility maximization. Selecting the best nested structure where particular cross elasticities can be ignored can involve the search across a large number of tree structures. The HEV model can assist in revealing a preferred nested structure through the distribution of the scale parameters across the alternatives.

THE EMPIRICAL CONTEXT

The prime focus is on evaluating new time-based bus tickets in the presence and absence of existing ticket offerings of a sample of non-concessioners and concession/non-pensioners in the Newcastle Bus Operations Area. Given the interest in evaluating sizeable variations in the levels of existing fares as well as the introduction of new fare categories, we use stated choice methods in combination with a knowledge of current modal/ticket attributes from revealed preference data to assess the ticket and mode choices made by a sample of residents (either car or bus users).

In the survey, respondents are asked to think about the last trip they made, where they went, how they traveled, how much it cost, etc., then are asked to describe another way they could have made that trip if their current mode were not available. Recognizing that the major forms of transport in Newcastle are car and bus, the survey limited the choice of current and alternative modes for all respondents to either bus or car. The stated preference component of the survey varies the new time-based tickets under a series of different pricing scenarios while assuming that the costs of the respondents' current form of travel is the same (see figure 1). Their responses to these different scenarios are recorded in terms of whether they choose to use their current mode/ticket (including car) or one of the new time-based tickets.

Sampling Strategy

A sample was designed that captured a sufficient number of travelers currently choosing bus or car modes and the available current ticket types. Using the distribution in table 1, it was necessary to collapse the bus ticket categories down to those most frequently used; namely, Single and TravelTen/TravelPass.

The sample size is 400 (expanded to 1,600 given 4 replications per person), with half being non-concession holders and half being concession/non-pension holders. Four suburbs in Newcastle, which are typical representations of travel behaviors for all residents in the Newcastle Bus Operations Area, were selected and sampled in roughly equal proportions, as were car users and bus users. Another quota of the sample is to have roughly equal proportions of car and bus users traveling for short and long trips. Through consultation with Newcastle Bus and Ferry Services, a short trip was defined as less than or equal to 5 km by car or less than or equal to 12 minutes by bus. It was also required that roughly equal proportions of bus users traveled on Single tickets and on TravelTen/TravelPass.

A face-to-face home interview was undertaken. Survey start points were generated to specifically target bus routes to obtain a sufficient sample of

FIGURE 1 Example of a Showcard for a Non-Concessioner

Current Form of Travel or New Bus? Call Number–A1

1	2	3	4	5
Current form of travel	**New bus**	**New bus**	**New bus**	**New bus**
Same costs as now	1-hour ticket $1.50 (Includes all transfers)	4-hour ticket $3.00 (Includes all transfers)	Day ticket $4.50 (Includes all transfers)	Weekly ticket $18.00 (Includes all transfers)

bus users. The start points were generated by randomly choosing streets in each of the selected suburbs to be cluster sampled. The sample is "choice-based"; that is, the sampling unit is the mode (ticket type) to ensure there are enough sampled currently choosing each of the alternative modes/ticket types. The revealed preference choice set is corrected in estimation to reproduce the base market shares. This does not apply to the stated choice subset of alternatives.

In addition, all observations are weighted by the distribution of personal income for residents in the Newcastle Bus Operations Area as revealed in the 1991 Census of Population and Housing. Table 2 summarizes the distribution of personal income for the population (Newcastle Bus Operations Area) and for the sample, and the weights used in scaling the data to represent the population.

TABLE 1 Profile of Public Bus Users by Ticket Type

Ticket type	Adult %	Concession %
Cash		
1–2 sections	20.8	9.9
3–9 sections	28.7	13.3
10–15 sections	2.7	1.1
16–21 sections	0.4	0.2
TravelTen		
1–2 sections	15.6	9.1
3–9 sections	22.9	6.6
10–15 sections	1.5	0.2
16–21 sections	0.0	0.0
TravelPass		
Blue	3.5	1.2
Orange	3.3	0.7
Red	0.5	0.2
Pink	0.0	0.0
Yellow	0.0	0.0
Bus Tripper	0.1	0.0
Total	100.0	100.0

Source: Newcastle Buses Ticket Usage: Number of One-Way Bus Trips, 1995.

Developing the Stated Choice Experiment

In a combined RP/SP approach it is important to present individuals with a stated preference experiment that offers realistic scenarios. Fare elasticities are only valid within the bounds of the minimum and maximum fares presented in an SP experiment. A variation of 25% below and 50% above a base fare level was selected (table 3) as the limits believed by Newcastle Buses to be "politically" feasible. The choice experimental design is a one-quarter fraction of a 3^4. This produces nine fare scenarios for each concession and non-concession situation. Each respondent is presented with four randomly assigned scenarios. The experimental

TABLE 2 Annual Personal Income Distribution of Population and Sample and Weights Used

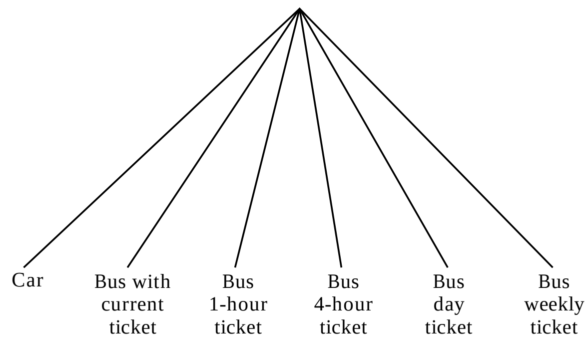
Annual personal income	Population %	Sample %	Weights
$0–$3,000	9.6	16.6	0.58
$3,001–$12,000	37.0	40.5	0.91
$12,001–$30,000	38.6	28.3	1.36
$30,001–$40,000	8.5	8.2	1.04
$40,001–$50,000	3.2	3.2	1.01
$50,001–$60,000	1.6	1.1	1.53
$60,001–$70,000	0.6	0.8	0.77
Over $70,000	0.9	1.3	0.64
Total	100.0	100.0	

Source: 1991 Census of Population and Housing.

TABLE 3 Full Range of Fares Used in Experiments

Ticket type	Low fare	Base fare	High fare
Concession/non-pensioners			
1-hour ticket	$0.75	$1.00	$1.50
4-hour ticket	$1.50	$2.00	$3.00
Day ticket	$2.25	$3.00	$4.50
Weekly ticket	$9.00	$12.00	$18.00
Non-concessioners			
1-hour ticket	$1.50	$2.00	$3.00
4-hour ticket	$3.00	$4.00	$6.00
Day ticket	$4.50	$6.00	$9.00
Weekly ticket	$18.00	$24.00	$36.00

FIGURE 2 The Universal Choice Set of Modes and Ticket Types



design is limited to the current mode/ticket used and the four proposed time-based ticket types for the bus—one-hour ticket, four-hour ticket, day ticket, and weekly ticket. A respondent is asked to select one of the four offered time-based tickets or their current mode. The fares for concession holders are exactly half that for non-concession holders. The current bus fares paid by respondents are not varied in the experiments.

The full set of alternatives analyzed are shown in figure 2. "Bus with current ticket" was modeled as two mutually exclusive alternatives—bus Single and bus TravelTen/TravelPass.

EMPIRICAL RESULTS

Table 4 provides a detailed breakdown of response rates. It was quite difficult to find respondents, especially those in the quota targets. It was particularly difficult to find respondents who traveled on buses using non-concession Single tickets and TravelTen or TravelPass for short distances (< 5 km or < 12 minutes). There was a high percentage of "non-quota" respondents, partly because those entitled to pensioner concession fares were not part of the sampling frame. Figure 3 gives the breakdown of useable responses by concession/ non concession, by trip length (short/long), and by ticket and mode.

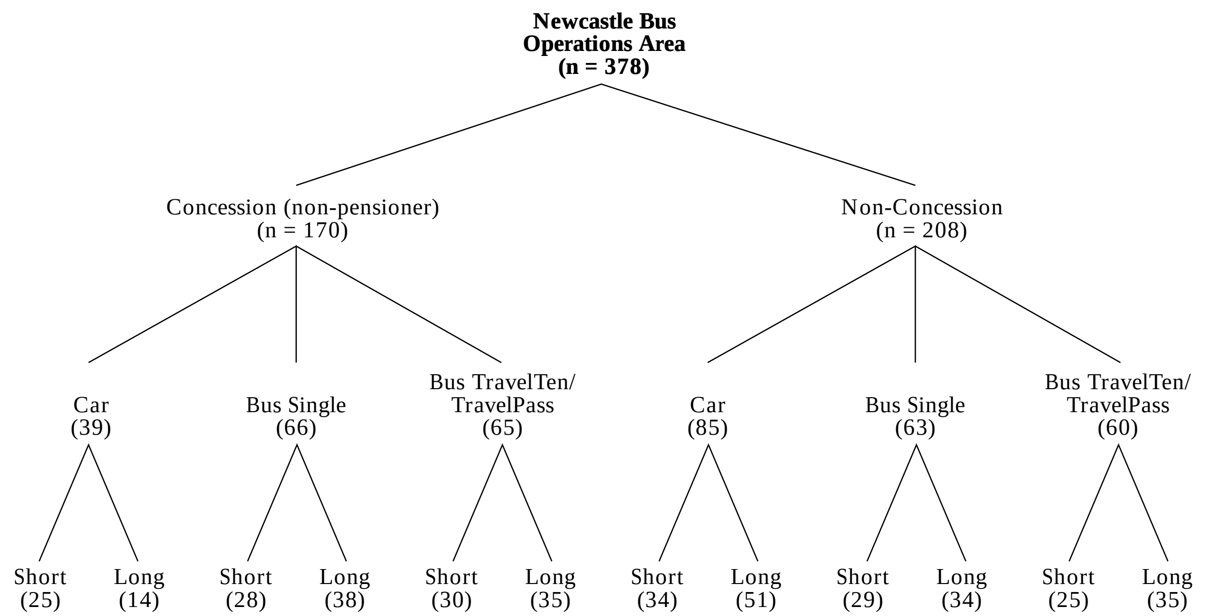
It must be noted that the sample sizes in figure 3 refer to actual interviews; the number of individuals having each RP alternative in their choice set is much higher. In addition, when the RP data is combined with the SP data we expanded the RP data to equivalence the number of SP replications. The decision on how to match the RP data with each SP replication is essentially Bayesian (Keane et al In press)—we have chosen to give them equal weight. The descriptive statistics for the estimation sample are summarized in Appendix A. When SP replications are pooled together with RP data, the possibility for serial correlation and state dependence exists. This issue has been recognized in the extant literature (e.g., Morikawa 1994). Morikawa suggests that inertia dummy variables representing actual RP choices be included in the SP utility expressions to ". . . absorb unobserved factors related to the preference of certain alternatives over others" (p. 164) as a way of approximating the presence of state dependence. We, however, found no statistical significance on the set of inertia dummies. We have not tested for serial correlation, which if it exists may lead to possible biases in the taste weights. We did, however, run a model with only the first SP replication and compared the taste weights and found no statistical significance. This finding is confirmed in unpublished work by Brownstone (1997).

TABLE 4 Response Rates

Response	Number	Percent
Not at home	509	23
Refusals	304	14
Call backs	24	1
Other	28	1
Non-quota	952	43
Interviews	398	18

The sample has been scaled using external data to represent the population. The profile of current mode and ticket is largely governed by the sampling strategy, where 33% of respondents are current car users, 33% are bus TravelTen or TravelPass

FIGURE 3 Breakdown of Fully Completed Interviews



users, and 34% are bus Single users. For the current car users, if the car were not available to them, 73% chose the bus Single ticket. Of current bus users, 67% will use the car as an alternative.

Tables 5 and 6 summarize the responses to the experiment. Table 5 shows choices made by respondents across the whole sample, broken down by their current mode/ticket. Of the respondents, 41% (6.5% bus Single, 15.2% bus TravelTen/TravelPass, and 19.3% car) did not switch from their current mode/ticket when presented with the new bus time-based fare options in the SP experiment. The one-hour ticket seems to be the most popular of the time-based bus fares, being the one chosen most by those who did not choose their current mode/ticket in the SP experiment. Of the respondents, 23.7% (i.e., 8.2% current bus Single, 7.3% current bus TravelTen/TravelPass, and 8.2%

TABLE 5 Current Mode/Ticket and Mode Chosen/Ticket in SP Experiment
(Based on weighted data)

	Current mode/ticket (in percent)			
Chosen mode/ ticket (SP)	**Bus Single**	**Bus TravelTen/ TravelPass**	**Car**	**Total**
Bus Single	6.5	0.0	0.0	6.5
Bus TravelTen/ TravelPass	0.0	15.2	0.0	15.2
Car	0.0	0.0	19.3	19.3
1-hour ticket	8.2	7.3	8.2	23.7
4-hour ticket	5.2	2.7	2.7	10.5
Day ticket	7.3	3.4	2.2	13.0
Weekly ticket	5.2	5.1	1.5	11.8
Total	32.5	33.6	33.9	100.0

TABLE 6 Current Mode/Ticket and Mode Chosen/Ticket in SP Experiment
(Based on weighted data)

	Current mode/ticket (in percent)		
Chosen mode/ ticket (SP)	**Bus Single**	**Bus TravelTen/ TravelPass**	**Car**
Bus Single	20.0	0.0	0.0
Bus TravelTen/ TravelPass	0.0	45.1	0.0
Car	0.0	0.0	57.0
1-hour ticket	25.3	21.6	24.1
4-hour ticket	16.0	8.0	7.9
Day ticket	22.6	10.2	6.6
Weekly ticket	16.1	15.1	4.5
Total	100.0	100.0	100.0

TABLE 7a Current Mode/Ticket and Mode/Ticket Chosen in SP Experiment for Concession: Short Trips
(Based on weighted data)

Chosen mode/ticket (SP)	Current mode/ticket (in percent)		
	Bus Single	Bus TravelTen/TravelPass	Car
Bus Single	25.9	0.0	0.0
Bus TravelTen/TravelPass	0.0	37.9	0.0
Car	0.0	0.0	74.0
1-hour ticket	21.9	15.0	12.3
4-hour ticket	13.2	10.7	5.1
Day ticket	25.0	10.5	7.1
Weekly ticket	14.0	25.8	1.4
Total	100.0	100.0	100.0

TABLE 7b Current Mode/Ticket and Mode/Ticket Chosen in SP Experiment for Concession: Long Trips
(Based on weighted data)

Chosen mode/ticket (SP)	Current mode/ticket (in percent)		
	Bus Single	Bus TravelTen/TravelPass	Car
Bus Single	11.8	0.0	0.0
Bus TravelTen/TravelPass	0.0	35.6	0.0
Car	0.0	0.0	32.0
1-hour ticket	17.8	33.9	53.8
4-hour ticket	15.5	7.2	0.0
Day ticket	28.7	10.6	7.8
Weekly ticket	26.1	12.6	6.4
Total	100.0	100.0	100.0

current car users) chose to travel by bus using the one-hour ticket.

Table 6 shows the breakdown of the choices made within each group of current mode/ticket classification. It shows that more than half (57%) of the current car users (current car users made up 32.8% of the sample) did not switch to using bus when presented with the new bus ticket options in the SP experiment. However, the remaining 43% of the current car users chose one of the time-based bus fares in the SP experiment. This implies that there is potential to attract current car users to the bus given the right conditions (e.g., fare levels, service level, etc.) since almost half of the current car users have indicated a willingness to switch to or consider traveling by bus using the new time-based fares.

Tables 7 and 8 look at the ticket choice more closely by stratifying into concession and non-concession, and short and long trips. Comparing tables 7 and 8 shows some interesting results. Most people who are using cars for short trips, even though they hold concession passes for public transport, are not willing to change to public transport. In contrast, their counterparts using cars for long trips are more willing to change to public transport. With current car users, the most popular time-based ticket is the one-hour ticket.

TABLE 8a Current Mode/Ticket and Mode/Ticket Chosen in SP Experiment for Non-Concession (Non-Pensioner): Short Trips
(Based on weighted data)

Chosen mode/ticket (SP)	Current mode/ticket (in percent)		
	Bus Single	Bus TravelTen/TravelPass	Car
Bus Single	24.3	0.0	0.0
Bus TravelTen/TravelPass	0.0	71.3	0.0
Car	0.0	0.0	57.5
1-hour ticket	34.3	8.1	26.0
4-hour ticket	10.8	5.9	9.3
Day ticket	14.9	8.1	4.7
Weekly ticket	15.7	6.6	2.5
Total	100.0	100.0	100.0

TABLE 8b Current Mode/Ticket and Mode/ Ticket Chosen in SP Experiment for Non-Concession (Non-Pensioner): Long Trips
(Based on weighted data)

Chosen mode/ticket (SP)	Current mode/ticket (in percent)		
	Bus Single	Bus TravelTen/TravelPass	Car
Bus Single	19.6	0.0	0.0
Bus TravelTen/TravelPass	0.0	40.2	0.0
Car	0.0	0.0	54.7
1-hour ticket	27.2	25.0	21.2
4-hour ticket	22.9	8.1	10.0
Day ticket	21.6	11.0	7.4
Weekly ticket	8.7	15.6	6.7
Total	100.0	100.0	100.0

Generally, most respondents using bus Singles for both short and long trips, are willing to switch to the time-based tickets offered. A higher proportion of the current bus TravelTen or TravelPass users in comparison to the current bus Singles users chose their current ticket instead of the time-based tickets. The final model results are given in table 9. Summary statistics of the estimation sample are given in Appendix A.

All four choice models have high explanatory power for a non-linear logit model as measured by pseudo r^2 values, varying from 0.550 to 0.598. The scale parameters vary quite a lot across the alternatives for each market, and despite the number of non-statistically significant scale parameters, there are sufficient significant parameters to suggest that a simple MNL model would confound taste and scale. If we look at short non-concession trips, we see similar mean estimates for scale parameters for one-hour bus and bus Single tickets, which is an appealing result given the expectation that there might be common unobserved influences. The same relationship holds in all four markets. However, in the long non-concession market the scale parameters are similar for one- and four-hour tickets, Single, and TravelTens, although the level of statistical significance is below acceptable levels except for a one-hour bus ticket. The ranking of the magnitudes of the scale parameters are very similar across trip lengths within each market of concession and non-concession travelers, but quite different between the two segments. The absolute levels of scale cannot be directly compared because the models are independently estimated.

We investigated the possible role of trip purpose, setting commuting trips as the base (exclude) purpose, and assigning the three trip-purpose dummy variable to all of the bus alternatives. With the exception of shopping trips for long concession trips, which has a significant downward shift effect on the probability of choosing bus (i.e., the probability of car use is higher for shopping trips in this market segment), trip purpose has no significant role.

Travel time and cost were estimated as generic both within each RP and SP data set and between the data sets. There is no microeconomic theoretical reason for treating them as data set specific, which has traditionally been the assumption in both sequential and joint estimation of SP-RP models resulting in a single scale parameter attributed to all alternatives in a specific data set (e.g., Morikawa 1989; Swait et al 1994). However, the joint estimation takes into account possible differences in scale in order to ensure that the final set of taste weights (parameter estimates) in table 9 are not confounded with scale. Differences in measurement error between the RP and SP data are accommodated in the scale parameter when a generic specification across the RP and SP alternatives is imposed.

The four models contain the set of parameter estimates for the RP model enriched by the SP data, to enable estimation of the matrices of direct and cross share price elasticities, reported in the next section. Importantly, the weighted aggregate elasticities (with choice probability weights) are derived from the RP model for the observed tickets types and car, enriched by the new time-based tickets drawn from the SP model system. The elements of an elasticity calculation are the predicted choice probability (which makes little sense in the stand-alone SP subset), the taste weights and scale parameters, and the attribute levels. The attribute levels used in calculating the elasticities reported in tables 10 and 11 are the levels used in model estimation across the sample.

Fare and Mode Elasticities

A number of mode/ticket type choice models were estimated for each travel market segment. The stated choice experiment provided the richness required for testing each market segment's sensitivity to varying levels of fares for each time-based ticket type. The parameter estimates for fares and car costs when transferred to the revealed preference model and rescaled enabled us to derive the appropriate matrix of direct and cross elasticities. Relaxation of the constant variance assumption of the standard multinomial logit model allows the cross elasticities to be alternative specific.

The final (8) sets of recommended direct and cross elasticities, based on the full sample of 378 interviews, are reported in tables 10 and 11. In reporting the results, we recognize that some of the explanatory variables in the models are marginally significant or not at all; however, the cost

TABLE 9 HEV Model: Joint Estimation of SP and RP Choices
a. Non-Concession Short Trips

Attribute	Units	Alternative	SP parameter estimates	t-value	RP parameter estimates	t-value
One-way trip cost	Dollars	All	–0.169098	–1.76	–0.169098	–1.76
Door-to-door time	Mins	All	–0.0052118	–1.54	–0.0052118	–1.54
Social-recreation trips	1,0	Bus	0.1481	0.76	0.1481	0.76
Shopping trips	1,0	Bus	–0.01907	-0.12	-0.01907	–0.12
Student trips	1,0	Bus	–0.16740	-0.94	-0.16740	–0.94
Bus Single constant		BusS	3.1638	9.22	2.3681	7.43
Bus TravelTen/ TravelPass constant		BusTT	3.5776	13.70		
Bus 1-hour constant		Bus1	3.2627	9.26		
Bus 4-hour constant		Bus4	2.9060	5.22		
Bus day ticket constant		BusDay	2.9667	5.41		
Car constant		Car	2.8706	5.27	4.3980	6.43
Scale parameters						
Bus 1-hour ticket (SP)		Bus1	0.194	1.65		
Bus 4-hour ticket (SP)		Bus4	0.341	1.75		
Bus day ticket (SP)		BusDay	0.405	1.98		
Bus weekly ticket (SP)		BusW	1.283	fixed		
Bus Single		BusS	0.181	2.73	0.709	1.54
Bus TravelTen/TravelPass		BusTT	0.289	1.87	0.249	1.04
Car		Car	0.523	1.54	0.536	1.15
Sample size		704				
Log-likelihood at converg.		–675.73				
Pseudo r-squared		0.598				

TABLE 9 HEV Model: Joint Estimation of SP and RP Choices
b. Non-Concession Long Trips

Attribute	Units	Alternative	SP parameter estimates	t-value	RP parameter estimates	t-value
One-way trip cost	Dollars	All	-0.082095	–2.12	–0.082095	–2.12
Door-to-door time	Mins	All	-0.0022177	–1.76	–0.0022177	–1.76
Social-recreation trips	1,0	Bus	-0.11718	–1.04	–0.11718	–1.04
Shopping trips	1,0	Bus	0.32926	1.38	0.32926	1.38
Student trips	1,0	Bus	-0.24737	–1.65	–0.24737	–1.65
Bus Single constant		BusS	3.2019	8.24	2.5887	6.79
Bus TravelTen/ TravelPass constant		BusTT	3.3262	8.65	2.4353	5.45
Bus 1-hour constant		Bus1	3.2378	9.326		
Bus 4-hour constant		Bus4	3.1318	8.49		
Bus day ticket constant		BusDay	3.1905	8.53		
Car constant		Car	2.9742	6.79	4.3219	4.59
Scale parameters						
Bus 1-hour ticket (SP)		Bus1	0.183	2.16		
Bus 4-hour ticket (SP)		Bus4	0.198	1.59		
Bus day ticket (SP)		BusDay	0.207	1.53		
Bus weekly ticket (SP)		BusW	1.283	fixed		
Bus Single		BusS	0.193	1.54	0.358	1.67
Bus TravelTen/TravelPass		BusTT	0.193	1.28	0.661	1.87
Car		Car	0.479	1.75	0.372	1.14
Sample size		960				
Log-likelihood at converg		–1056.8				
Pseudo r-squared		0.550				

TABLE 9 HEV Model: Joint Estimation of SP and RP Choices
c. Concession Short Trips

Attribute	Units	Alternative	SP parameter estimates	t-value	RP parameter estimates	t-value
One-way trip cost	Dollars	All	–0.36005	–1.96	–0.36005	–1.96
Door-to-door time	Mins	All	–0.02896	–1.86	–0.02896	–1.86
Social-recreation trips	1,0	Bus	0.76731	1.67	0.76731	1.67
Shopping trips	1,0	Bus	–0.06571	–0.56	–0.06571	–0.56
Student trips	1,0	Bus	0.3185	1.54	0.3185	1.54
Bus Single constant		BusS	2.7153	11.36	2.7153	11.36
Bus TravelTen/ TravelPass constant		BusTT	2.7793	12.71	2.4388	9.45
Bus 1-hour constant		Bus1	2.6863	10.54		
Bus 4-hour constant		Bus4	2.4675	6.24		
Bus day ticket constant		BusDay	2.8585	12.56		
Car constant		Car	2.5796	8.39	3.0254	4.77
Scale parameters						
Bus 1-hour ticket (SP)		Bus1	0.221	1.54		
Bus 4-hour ticket (SP)		Bus4	0.314	1.53		
Bus day ticket (SP)		BusDay	0.173	1.65		
Bus weekly ticket (SP)		BusW	1.28	fixed		
Bus Single		BusS	0.174	1.32	0.672	1.87
Bus TravelTen/TravelPass		BusTT	0.171	1.96	0.307	1.21
Car		Car	0.529	1.79	0.451	1.55
Sample size		664				
Log-likelihood at converg		–581.78				
Pseudo r-squared		0.588				

TABLE 9 HEV Model: Joint Estimation of SP and RP Choices
d. Concession Long Trips

Attribute	Units	Alternative	SP parameter estimates	t-value	RP parameter estimates	t-value
One-way trip cost	Dollars	All	–0.22005	–2.12	–0.22005	–2.12
Door-to-door time	Mins	All	–0.02135	–1.97	–0.02135	–1.97
Social-recreation trips	1,0	Bus	0.5462	1.67	0.5462	1.67
Shopping trips	1,0	Bus	–0.08761	–.2.1	–0.08761	–0.21
Student trips	1,0	Bus	0.4236	1.74	0.4236	1.74
Bus Single constant		BusS	2.9523	11.36	2.3114	9.42
Bus TravelTen/ TravelPass constant		BusTT	2.3289	12.71	1.8965	7.66
Bus 1-hour constant		Bus1	2.7789	9.43		
Bus 4-hour constant		Bus4	3.1243	5.32		
Bus day ticket constant		BusDay	3.5632	11.29		
Bus weekly constant		BusW	2.3429	7.46	3.0122	6.88
Scale parameters						
Bus 1-hour ticket (SP)		Bus1	0.174	1.43		
Bus 4-hour ticket (SP)		Bus4	0.329	1.87		
Bus day ticket (SP)		BusDay	0.139	1.66		
Bus weekly ticket (SP)		BusW	1.28	fixed		
Bus Single		BusS	0.153	1.73	0.694	1.95
Bus TravelTen/TravelPass		BusTT	0.214	1.90	0.332	1.55
Car		Car	0.631	1.81	0.476	1.73
Sample size	696					
Log-likelihood at converg	–572.78					
Pseudo r-squared	0.593					

taste weights are statistically significant at the 95% level for concession trips and non-concession long trips, and "acceptable" at a t-value of –1.76 for non-concession short trips. The inclusion/exclusion of the non-significant effects has little impact on the derived probabilities or the taste weights for cost, and thus we are confident that the resulting elasticity matrices are minimally affected by the presence of statistically insignificant influences in table 9. The sets of the direct and cross elasticities are for only two scenarios. The first scenario comprises the car and the four time-based tickets: the situation whereby with the introduction of time-based tickets, bus Singles, TravelTens, and TravelPasses are no longer sold. The second scenario is where bus Singles for short trips are still kept but TravelTens and TravelPasses are no longer offered with the introduction of the time-based tickets.

In Table 10, each column provides one direct share elasticity and four cross share elasticities, while in table 11, each column provides one direct share elasticity and five cross share elasticities. A direct or cross elasticity represents the relationship between a percentage change in fare level and a percentage change in the proportion of daily one-way trips by the particular mode or ticket type. For example, the column headed "one-hour ticket" in the Concession Short Trips section for Scenario 1 tells us that a 1% increase in the one-hour ticket fare leads to a 1.153% reduction in the proportion of daily one-way trips by bus on a one-hour ticket. In addition, this 1% single fare increase is "distributed" among the competing alternatives according to the set of cross elasticities, normalized to sum to 1.

These results have many implications, especially for a fares policy. There is very little switching between car and bus options, with most switching occurring within the bus options. Looking at the direct elasticities, it can be seen that in general,

TABLE 10. Scenario 1: Elasticities for Concession and Non-Concession Markets

	Car	1-hour ticket	4-hour ticket	Day ticket	Weekly ticket
a. Concession: short trips					
Car	–0.200	0.296	0.298	0.422	0.370
1-hour ticket	0.047	–1.153	0.278	0.600	0.305
4-hour ticket	0.049	0.269	–1.165	0.434	0.293
Day ticket	0.056	0.297	0.301	–1.825	0.334
Weekly ticket	0.046	0.288	0.287	0.369	–1.301
b. Concession: long trips					
Car	–0.192	0.055	0.091	0.080	0.300
1-hour ticket	0.040	–0.299	0.102	0.330	0.200
4-hour ticket	0.020	0.074	–0.464	0.042	0.278
Day ticket	0.040	0.080	0.105	–0.551	0.240
Weekly ticket	0.088	0.090	0.166	0.102	–1.020
c. Non-concession: short trips					
Car	–0.068	0.280	0.088	0.195	0.270
1-hour ticket	0.024	–1.520	0.420	0.397	0.480
4-hour ticket	0.013	0.420	–1.010	0.321	0.402
Day ticket	0.020	0.390	0.212	–1.239	0.297
Weekly ticket	0.015	0.430	0.290	0.323	–1.450
d. Non-concession: long trips					
Car	–0.600	0.230	0.260	0.350	0.353
1-hour ticket	0.120	–1.200	0.310	0.420	0.396
4-hour ticket	0.170	0.250	–1.290	0.460	0.431
Day ticket	0.140	0.340	0.350	–1.770	0.445
Weekly ticket	0.170	0.380	0.370	0.540	–1.620

Note: Read for mode/ticket as column.

TABLE 11. Scenario 2: Elasticities for Concession and Non-Concession Markets (plus tables 10b and 10c)

	Bus Single	Car	1-hour ticket	4-hour ticket	Day ticket	Weekly ticket
Concession: short trips						
Bus Single	–1.020	0.000	0.300	0.314	0.464	0.364
Car	0.060	–0.099	0.040	0.024	0.042	0.042
1-hour ticket	0.249	0.030	–1.138	0.410	0.520	0.433
4-hour ticket	0.244	0.030	0.320	–1.473	0.532	0.445
Day ticket	0.241	0.022	0.258	0.373	–2.019	0.360
Weekly ticket	0.230	0.022	0.219	0.351	0.460	–1.643
Non-concession: short trips						
Bus Single	–1.501	0.001	0.375	0.254	0.454	0.466
Car	0.059	-0.070	0.189	0.054	0.083	0.096
1-hour ticket	0.431	0.022	–1.145	0.256	0.455	0.497
4-hour ticket	0.274	0.012	0.140	–0.906	0.315	0.331
Day ticket	0.331	0.017	0.201	0.164	–1.690	0.387
Weekly ticket	0.401	0.020	0.241	0.179	0.381	–1.776

Note: Read for mode/ticket as column.

except in the Non Concession Short Trips market, sensitivity increases as time validity of the time-based fares increases. This has interesting implications for a fares policy, as it means that a decrease in the longer time-based fares purchase is quite substantial with a fare increase compared with the shorter time-based fares. Also, increasing the price of the one-hour ticket offers higher revenue growth prospects for smaller losses in patronage than in the case of day and weekly tickets.

The direct elasticities for long concession trips are lower compared with the short trips. This implies that the concession passengers traveling for long trips are less sensitive to fare changes than their counterparts who are doing short trips. For the non-concession market, those undertaking short trips are very sensitive to changes in fares for the one-hour ticket; while the four-hour ticket has the lowest (short trips) and second lowest (long trips) elasticity among the time-based fares. The implication is that the four-hour ticket is perceived as a better value for money; given the flexibility, one buys for the price and the number of trips that can be made while the ticket is valid.

In the case where bus Singles for short trips are still offered with the introduction of the time-based fares, the concession passengers are less sensitive to changes in fare for bus Singles. This shows that the bus Single is still the best value for passengers traveling short distances on concession. The reason may be that they generally undertake outings with shorter elapsed time before returning.

CONCLUSIONS

The results reported here are based on estimation of stated and revealed choice data, where the variances of the unobserved components of the indirect utility expressions associated with each of the modal and ticketing alternatives are different. The taste weights attached to fares in the stated choice model have been rescaled by the ratio of the variances associated with fare for a particular alternative across the two model systems, so that the richness of the fare data in the stated choice experiment enriches the market model. The resulting matrix of direct and cross elasticities reflects the market environment in which concession and non-concession travelers make choices while benefiting by an enhanced understanding of how travelers respond to fare profiles not always observed in real markets, but including timed-fare profiles that are of interest as potential alternatives to the current market offerings.

A better understanding of market sensitivity to classes of tickets is promoted as part of the improvement in management practices designed to improve fare yields. The matrices of elasticities are input as the behavioral base into a decision support system used to evaluate the implications on revenue and patronage of alternative fare scenarios in respect to mixtures of ticket types and levels of fares.

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Appendix A.

Summary Sample Statistics for the Four Market Segments

(Standard deviations in parenthesis)

a. Short Concession Trips

Stated preference sub-sample	Out-of pocket cost ($)	Main mode time (mins)	Access+egress time (mins)	Car available (proportion)	Sample size
ALTERNATIVE					
Total sample					
Bus 1-hour ticket	1.08 (0.31)	10.42 (5.95)	6.90 (5.69)	0.120	332
Bus 4-hour ticket	1.07 (0.30)	10.42 (5.95)	6.90 (5.69)	0.120	332
Bus day ticket	1.53 (0.36)	10.42 (5.95)	6.90 (5.69)	0.120	332
Bus weekly ticket	1.25 (0.28)	10.42 (5.95)	6.90 (5.69)	0.120	332
Bus Single	0.97 (0.32)	8.68 (2.34)	6.00 (5.40)	0.179	112
Bus TravelTen/TravelPass	0.65 (0.23)	8.70 (2.43)	7.47 (6.36)	0.167	120
Car	0.30 (0.11)	8.00 (3.28)	– –	–	100
Sample who chose that alternative					
Bus 1-hour ticket	0.91 (0.24)	11.85 (7.40)	5.95 (4.32)	0.130	54
Bus 4-hour ticket	0.91 (0.22)	8.56 (2.34)	6.89 (4.08)	0.194	36
Bus day ticket	1.32 (0.27)	10.04 (5.67)	8.74 (7.70)	0.120	50
Bus weekly ticket	1.12 (0.23)	9.43 (5.76)	7.89 (6.81)	0.149	47
Bus Single	0.78 (0.30)	7.82 (2.40)	4.29 (2.85)	0.357	28
Bus TravelTen/TravelPass	0.54 (0.19)	8.05 (2.81)	6.27 (5.15)	0.068	44
Car	0.28 (0.11)	7.70 (3.32)	– –	–	73

Revealed preference sub-sample	Out-of pocket cost ($)	Main mode time (mins)	Access+egress time (mins)	Car available (proportion)	Sample size
ALTERNATIVE					
Total sample					
Bus Single	1.069 (0.42)	11.20 (6.90)	6.78 (5.3)	0.111	180
Bus TravelTen/TravelPass	0.646 (0.22)	9.50 (4.38)	7.05 (6.13)	0.132	152
Car	0.357 (0.20)	8.05 (4.55)	– –	–	332
Sample who chose that alternative					
Bus Single	0.97 (0.32)	8.68 (2.34)	6.00 (5.4)	0.179	112
Bus TravelTen/TravelPass	0.65 (0.23)	8.70 (2.43)	7.47 (6.4)	0.167	120
Car	0.302 (0.11)	8.00 (3.28)	– –	–	100

b. Long Concession Trips

Stated preference sub-sample	Out-of pocket cost ($)	Main mode time (mins)	Access+egress time (mins)	Car available (proportion)	Sample size
ALTERNATIVE					
Total sample					
Bus 1-hour ticket	1.085 (0.32)	35.60 (21.5)	8.28 (6.23)	0.218	348
Bus 4-hour ticket	1.084 (0.31)	35.60 (21.5)	8.28 (6.23)	0.218	348
Bus day ticket	1.529 (0.36)	35.60 (21.5)	8.28 (6.23)	0.218	348
Bus weekly ticket	1.235 (0.29)	35.60 (21.5)	8.28 (6.23)	0.218	348
Bus Single	1.47 (0.62)	35.26 (20.9)	10.05 (6.6)	0.342	152
Bus TravelTen/TravelPass	1.01 (0.53)	33.51 (22.2)	6.89 (5.9)	0.171	140
Car	1.07 (0.39)	17.14 (6.8)	– –	–	56
Sample who chose that alternative					
Bus 1-hour ticket	0.942 (0.26)	42.08 (24.6)	8.58 (7.09)	0.212	104
Bus 4-hour ticket	0.882 (0.20)	40.00 (18.9)	10.15 (8.13)	0.294	34
Bus day ticket	1.35 (0.30)	38.93 (26.4)	9.59 (6.58)	0.279	61
Bus weekly ticket	1.14 (0.27)	32.46 (18.2)	7.22 (4.56)	0.159	63
Bus Single	1.25 (0.0)	28.22 (9.9)	9.50 (5.9)	0.333	18
Bus TravelTen/TravelPass	0.802 (0.16)	22.78 (9.1)	5.25 (3.9)	0.224	49
Car	0.94 (0.18)	15.53 (2.8)	– –	–	19

Revealed preference sub-sample	Out-of pocket cost ($)	Main mode time (mins)	Access+egress time (mins)	Car available (proportion)	Sample size
ALTERNATIVE					
Total sample					
Bus Single	1.61 (0.81)	35.44 (19.6)	9.24 (6.43)	0.283	184
Bus TravelTen/TravelPass	0.991 (0.55)	35.78 (23.4)	7.20 (5.83)	0.146	164
Car	0.997 (0.51)	16.59 (8.1)	– –	–	348
Sample who chose that alternative					
Bus Single (RP)	1.47 (0.62)	35.26 (20.9)	10.05 (6.60)	0.342	152
Bus TravelTen/TravelPass	1.10 (0.53)	33.51 (22.2)	6.89 (5.93)	0.171	140
Car	1.074 (0.39)	17.14 (6.8)	– –	–	56

c. Short Non-Concession Trips

Stated preference sub-sample	Out-of pocket cost ($)		Main mode time (mins)		Access+egress time (mins)		Car available (proportion)	Sample size
ALTERNATIVE								
Total sample								
Bus 1-hour ticket	2.17	(0.62)	11.67	(5.87)	7.68	(5.91)	0.114	352
Bus 4-hour ticket	2.18	(0.62)	11.67	(5.87)	7.68	(5.91)	0.114	352
Bus day ticket	3.10	(0.74)	11.67	(5.87)	7.68	(5.91)	0.114	352
Bus weekly ticket	2.44	(0.58)	11.67	(5.87)	7.68	(5.91)	0.114	352
Bus Single	1.93	(0.62)	10.38	(2.41)	8.55	(6.14)	0.207	116
Bus TravelTen/TravelPass	1.25	(0.40)	9.88	(2.35)	6.68	(5.35)	0.160	100
Car	0.28	(0.12)	8.09	(4.28)	–	–	–	136
Sample who chose that alternative								
Bus 1-hour ticket	1.85	(0.45)	12.41	(7.70)	7.94	(6.33)	0.084	83
Bus 4-hour ticket	1.85	(0.49)	14.12	(7.46)	9.35	(6.29)	0.147	34
Bus day ticket	2.78	(0.64)	11.14	(4.91)	7.27	(6.62)	0.216	37
Bus weekly ticket	2.07	(0.47)	10.85	(2.21)	7.59	(7.63)	0.111	27
Bus Single	1.71	(0.63)	9.30	(2.09)	8.97	(4.67)	0.267	30
Bus TravelTen/TravelPass	1.27	(0.40)	9.85	(2.29)	6.66	(5.09)	0.134	67
Car	0.27	(0.12)	7.74	(4.44)	–	–	–	74

Revealed preference sub-sample	Out-of pocket cost ($)		Main mode time (mins)		Access+egress time (mins)		Car available (proportion)	Sample size
ALTERNATIVE								
Total sample								
Bus Single	1.80	(0.76)	12.33	(6.77)	8.16	(6.13)	0.103	232
Bus TravelTen/TravelPass	1.27	(0.42)	10.40	(3.21)	6.77	(5.36)	0.133	120
Car	0.34	(0.16)	8.05	(4.01)	–	–	–	352
Sample who chose that alternative								
Bus Single	1.93	(0.62)	10.38	(2.41)	8.55	(6.14)	0.207	116
Bus TravelTen/TravelPass	1.25	(0.40)	9.88	(2.35)	6.68	(5.35)	0.160	100
Car	0.28	(0.12)	8.09	(4.28)	–	–	–	136

d. Long Non-Concession Trips

Stated preference sub-sample	Out-of pocket cost ($)	Main mode time (mins)	Access+egress time (mins)	Car available (proportion)	Sample size
ALTERNATIVE					
Total sample					
Bus 1-hour ticket	2.15 (0.62)	38.88 (24.4)	10.68 (10.4)	0.133	480
Bus 4-hour ticket	2.16 (0.63)	38.88 (24.4)	10.68 (10.4)	0.133	480
Bus day ticket	3.11 (0.72)	38.88 (24.4)	10.68 (10.4)	0.133	480
Bus weekly ticket	2.51 (0.58)	38.88 (24.4)	10.68 (10.4)	0.133	480
Bus Single (RP)	2.56 (0.78)	31.91 (18.4)	9.91 (10.1)	0.206	136
Bus TravelTen/TravelPass	1.65 (0.37)	36.66 (23.6)	8.66 (6.2)	0.257	140
Car	1.43 (1.02)	23.24 (13.6)	– –	–	204
Sample who chose that alternative					
Bus 1-hour ticket	1.83 (0.45)	36.34 (23.4)	9.15 (8.4)	0.103	117
Bus 4-hour ticket	1.88 (0.54)	41.54 (24.0)	8.40 (5.8)	0.206	63
Bus day ticket	2.63 (0.57)	43.14 (25.2)	9.31 (9.1)	0.136	59
Bus weekly ticket	2.08 (0.43)	36.40 (18.2)	11.23 (9.3)	0.208	48
Bus Single (RP)	2.49 (0.15)	30.08 (6.5)	7.50 (4.6)	0.231	26
Bus TravelTen/TravelPass	1.58 (0.32)	28.43 (13.9)	8.23 (5.6)	0.268	56
Car	1.47 (1.10)	24.98 (15.2)	– –	–	111

Revealed preference sub-sample	Out-of pocket cost ($)	Main mode time (mins)	Access+egress time (mins)	Car available (proportion)	Sample size
ALTERNATIVE					
Total sample					
Bus Single (RP)	2.76 (0.93)	37.73 (23.7)	11.83 (12.50)	0.101	276
Bus TravelTen/TravelPass	1.54 (0.51)	40.43 (25.3)	9.14 (6.10)	0.176	204
Car	1.22 (0.91)	19.95 (11.8)	– –	–	480
Sample who chose that alternative					
Bus Single	2.60 (0.78)	31.91 (18.4)	9.91 (10.14)	0.206	136
Bus TravelTen/TravelPass	1.65 (0.37)	36.66 (23.6)	8.66 (6.23)	0.257	140
Car	1.43 (1.00)	23.24 (13.6)	– –	–	204