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The Valuation of Travel Time Savings for Urban Car Drivers: Evaluating Alternative Model Specifications

By

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ABSTRACT: The empirical valuation of travel time savings is a derivative of the ratio of parameter estimates in a discrete choice model. The most common formulation (multinomial logit) imposes strong restrictions on the profile of the unobserved influences on choice as represented by the random component of a preference function. As we progress our ability to relax the restrictions we open up opportunities to benchmark the values derived from simple (albeit relatively restrictive) models. In this paper we contrast the values of travel time savings derived from five discrete choice models – multinomial logit, heteroskedastic extreme value, covariance heterogeneity logit, mixed (or random parameter) logit and multinomial probit. The empirical setting is urban car commuting and non-commuting in six locations in New Zealand. The evidence supports the growing position that less restrictive choice model specifications tend to produce higher estimates of values of time savings compared to the multinomial logit model; however the degree of under-estimation of multinomial logit remains quite variable, depending on the context.

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Introduction

A small but growing literature is sending signals that the popular multinomial logit (MNL) model tends to under-estimate the value of travel time savings (VTTS). Recent studies by Hensher (1997, forthcoming) and Bhat (1995) have found systematically higher VTTS for less restrictive discrete choice specifications such as the heteroskedastic extreme value model, the covariance heterogeneity logit model and mixed logit. If this directional tendency persists, it raises questions about the implied loss of user benefit from the application of MNL-based VTTS in project appraisal.

The earlier studies cited above are long distance intercity applications. The current paper investigates the extent to which the evidence on under-estimation transfers to urban travel. The empirical setting is urban car commuting and non-commuting in six locations in New Zealand. We contrast the values of travel time savings derived from multinomial logit (MNL), heteroskedastic extreme value (HEV), covariance heterogeneity logit (CovHet), mixed (or random parameter) logit (ML/RPL) and multinomial probit (MNP).

In deriving estimates of VTTS, we move beyond a focus on the heterogeneity of travel time that distinguishes between invehicle and out of vehicle time to a focus on the composition of invehicle time for car travel, distinguishing between free flow time, slowed down time and stop/start time. The value of congestion time savings, a topic of growing interest (eg Calfee and Winston 1998) is a mixture of the last two dimensions of travel time. In addition we account for the contingency time that a traveller includes in the face of uncertainty in respect of arrival time at a destination. Trip cost is disaggregated into running costs and tolls to recognise the broadening range of monetary costs that impact directly on a trip.

With a complex disaggregation of travel time and travel cost, revealed preference data (RP) is inappropriate. There is too much confoundment in RP data, best described as ‘dirty’ from the point of view of statistical estimation of the individual influences on choice. Furthermore some attributes such as a toll often do not exist or are of limited variability so we are unable to establish their influence. An alternative is a stated choice experiment in which we systematically vary combinations of levels of each attribute to reveal new opportunities relative to the existing circumstance of time-cost on offer. Through the experimental design paradigm we observe a sample of travellers making choices between the current trip attribute level bundle and other attribute level bundles. This approach is the preferred method of separating out the independent contributions of each time and cost component and hence is the preferred approach capable of providing disaggregated time values.

The paper is organised as follows. We begin with a discussion of the behavioural risks in imposing a simple structure on the utility expressions representing each alternative in a choice set. This reveals a number of alternative functional forms for the random components. The following section summarises the major behavioural properties of four less restrictive choice models - HEV, CovHet, ML/RPL and MNP. The next section describes the design of a stated choice experiment and a computer-based survey instrument to capture the empirical responses to alternative car driver travel scenarios for urban commuter and non-commuter trips. The remaining substantive sections present the empirical analysis with a focus on values of travel time savings, followed by a conclusion.

Beyond Simple Choice Models

There are many influences to take into account when studying and explaining the preferences and hence choice behaviour of individuals. Some of these influences are measured with great accuracy, some are measured with error and some are excluded. The set of unobserved influences to be accommodated in the estimation of the choice model might be correlated across the alternatives in the choice set (ie non-zero covariance). Furthermore when these potential sources of variability in preferences are taken into account, there may still remain additional sources of influence that are unique to each individual. Allowing for these idiosyncracies of individuals is known as accounting for unobserved heterogeneity.

The importance of a proper account of the treatment of the unobserved effects can be illustrated by the following example. Consider a simple random utility model, in which there are heterogeneous preferences for observed and unobserved attributes of alternative modes:

$$U_{qjt} = \alpha_{qj} + p_{qjt}\gamma_{q} + x_{qjt}\beta_{q} + \varepsilon_{qjt} \tag{1}$$

U_{qjt} is the utility that individual q receives given a choice of alternative j on occasion t. In an SC experiment, t would index choice tasks. p_{qjt} denotes price, and x_{qjt} denotes another observed attribute of j (which for complete generality varies across individuals and choice occasions). α_{qj} denotes the individual specific intercept for alternative j, arising from q's preferences for unobserved attributes of j. γ_q and β_q are individual specific utility parameters that are intrinsic to the individual and hence invariant over choice occasions. The ε_{qjt} can be interpreted as occasion-specific shocks to q's tastes, which for convenience are assumed to be independent over choice occasions, alternatives and individuals.

Suppose we estimate an MNL model, incorrectly assuming that the intercept and slope parameters are homogeneous in the population. The random component in this model will be

$$w_{qjt} = \hat{\alpha}_{q} + p_{qjt}\hat{\gamma}_{q} + x_{qjt}\hat{\beta}_{q} + \varepsilon_{qjt} \tag{2}$$

where ^ denotes the individual specific deviation from the population mean. Observe that (from the analyst's perspective) the variance of this error term for individual q on choice occasion t is

$$\operatorname{var}(w_{qjt}) = \sigma_{\alpha}^{2} + p_{qjt}^{2}\,\sigma_{\gamma}^{2} + x_{qjt}^{2}\,\sigma_{\beta}^{2} + \sigma_{\varepsilon}^{2} \tag{3}$$

and the covariance between choice occasions t and t–1 is

$$\operatorname{cov}(w_{qjt}, w_{qj,t-1}) = \sigma_{\alpha}^{2} + p_{qjt}\, p_{qj,t-1}\, \sigma_{\gamma}^{2} + x_{qjt}\, x_{qj,t-1} \sigma_{\beta}^{2} \tag{4}$$

Equations (3) and (4) reveal two interesting consequences of ignoring heterogeneity in preferences. First, the error variance will differ across choice occasions as the price *p* and attribute *x* are varied. If one estimates an MNL model with a constant error variance, this will show up as variation in the intercept and slope parameters across choice occasions. In an SC experiment context, this could lead to a false conclusion that there are order effects in the process generating responses.

Second, equation (4) shows how preference heterogeneity leads to serially correlated errors. That heterogeneity is a special type of serial correlation is not well understood in the transportation literature. To obtain efficient estimates of choice model parameters one should include a specification of the heterogeneity structure in the model such as respecification of the parameters associated with each attributes (including price) as random[1]. But more importantly, if preference heterogeneity is present it is not merely a statistical nuisance requiring correction. Rather, one should then model the heterogeneity in order to obtain accurate choice model predictions, because the presence of heterogeneity will impact on the marginal rates of substitution between attributes, and lead to IIA violations.

This discussion suggests the importance of paying attention to the behavioural source of the error terms in a choice model that may lead to new insights into how the model should be estimated, interpreted and applied. We have selected four less restrictive choice models to contrast with MNL[2].

Heteroskedastic extreme value (HEV) model - random effects HEV

The HEV model removes the condition of *identically distributed* random components associated with the MNL model while maintaining zero inter-alternative correlation. Bhat (1995) and Hensher (1998) amongst others, have implemented the HEV model. The probability density function and the cumulative distribution function of the random error term for the *i*th alternative with scale parameter λ_i for the HEV unobserved effects are given as Equation (5)

$$f(\varepsilon_i) = \frac{1}{\lambda_i} e^{-\frac{t_i}{\lambda_i}} e^{-e^{-\frac{\varepsilon_i}{\lambda_i}}} \text{ and } F_i(z) = \int_{\varepsilon_i=-\infty}^{\varepsilon_i=z} f(\varepsilon_i)\, d\varepsilon_i = e^{-e^{-\frac{z}{\lambda_i}}} \tag{5}$$

The probability that an individual will choose alternative *i* (P_i) from the set *C* of available alternatives is given in equation (6).

[1] The empirical evidence suggests that once unobserved heterogeneity is taken into account via a random effects specification such as ML or RPL, serial correlation is negligible or absent. That is, serial correlation is often spurious due to the failure to account for unobserved heterogeneity.
[2] We have excluded nested logit (other than its commonality with CovHet). Nested logit is a special case of the less restrictive models implemented in the text.

$$
\begin{aligned}
P_i &= \text{Prob}\,(U_i > U_j),\ \text{for all}\, j \neq i,\ j \in C \\
&= \text{Prob}\,(e_j \leq V_i - V_j + e_i),\text{for all}\, j \neq i,\ j \in C \\
&= \int_{e_i=-\infty}^{e_i=+\infty} \prod_{j\in C,\, j\neq i} F\left[\frac{V_i - V_j + e_i}{l_j}\right]\frac{1}{l_i}\, f\left(\frac{e_i}{l_i}\right)\mathrm{d}e_i\,,
\end{aligned}
\tag{6}
$$

where $f(\ .\ )$ and F(.) are the probability density function and cumulative distribution function of the standard type 1 extreme value distribution, respectively. If the scale parameters of the random components of all alternatives are equal, then the probability expression in equation (6) collapses to that of the multinomial logit.

The HEV model is flexible enough to allow differential substitution among all pairs of alternatives. When the observed utility of some alternative *l* changes, this affects the observed utility differential between another alternative *i* and the alternative *l*. However, this change in the observed utility differential is tempered by the unobserved random component of alternative *i*. The larger the scale parameter (or equivalently, the standard deviation) of the random error component for alternative *i*, the more tempered is the effect of the change in the observed utility differential and smaller is the elasticity effect on the probability of choosing alternative *i*.

Covariance heterogeneity (CovHet) logit: latent segmentation partitioned logit

Travel choice research focuses extensively on segmenting potential and actual choosers of each alternative in the offered choice set. There are two primary segmentation strategies - by benefit segment and by agents' characteristics. Sources of unobserved variance are candidates for identification through some functional mapping with characteristics of individuals as well as data-specific effects (eg task complexity, collection method). A few studies have implemented a latent class segmentation model within the framework of a set of partitioned MNL models (see Louviere et al in press and Swait 1994), or a nested logit framework within which the scale parameter (λ_{it}) varies between branches of the partitioned model but is invariant within a branch between alternatives ie $\lambda_i = \lambda_j\ \forall\ j\in J$ (McFadden 1981). A typical nested logit model is summarised in equations (7)-(13) (from Hensher and Greene 1999).

Ignoring the subscripts for an individual we define the three-level probability choice system:

$$P(k,j,i) = P(k|j,i)\times P(j|\text{i})\times P(i) \tag{7}$$

The choice probabilities for the *elemental alternatives* are defined as:

$$P(k \mid j,i) = \frac{\exp[\mathbf{b}'\,\mathbf{x}(k \mid j,i)]}{\sum_{l=1}^{K|j,i}\exp[b'\,\mathbf{x}(l \mid j,i)]} = \frac{\exp[\mathbf{b}'\,\mathbf{x}(k \mid j,i)]}{\exp[IV(j \mid i)]} \tag{8}$$

where $k|j,i$ = elemental alternative k in branch j of limb i, $K|j,i$ = number of elemental alternatives in branch j of limb i, and the inclusive value for branch j in limb i is

$$IV(j\,|\,i) = \log \sum_{k=1}^{K|j,i} \exp[\mathbf{b}'\mathbf{x}(k\,|\,j,i)] \qquad (9)$$

The *branch level* probability is

$$p(j\,|\,i) = \frac{\exp\{\lambda(j\,|\,i)[\mathbf{a}'\mathbf{y}(j\,|\,i) + IV(j\,|\,i)]\}}{\sum_{m=1}^{J|i} \exp\{\lambda(m\,|\,i)[\mathbf{a}'\mathbf{y}(m\,|\,i) + IV(m\,|\,i)]\}} = \frac{\exp\{\lambda(j\,|\,i)[\mathbf{a}'\mathbf{y}(j\,|\,i) + IV(j\,|\,i)]\}}{\exp[IV(i)]} \qquad (10)$$

where $j|i$ = branch j in limb i, $J|i$ = number of branches in limb i, and

$$IV(i) = \log \sum_{j=1}^{J|i} \exp\{\lambda(j\,|\,i)[\mathbf{a}'\mathbf{y}(j\,|\,i) + IV(j\,|\,i)]\} \qquad (11)$$

Finally, the *limb level* is defined by

$$p(i) = \frac{\exp\{\gamma(i)[\mathbf{c}'\mathbf{z}(i) + IV(i)]\}}{\sum_{n=1}^{I} \exp\{\gamma(n)[\mathbf{c}'\mathbf{z}(n) + IV(n)]\}} = \frac{\exp\{\gamma(i)[\mathbf{c}'\mathbf{z}(i) + IV(i)]\}}{\exp(IV)} \qquad (12)$$

where I = number of limbs in the three level tree and

$$IV = \log \sum_{i=1}^{I} \exp\{\gamma(i)[c'\mathbf{z}(i) + IV(i)]\} \qquad (13)$$

By normalising the value of the scale parameter at the lower level to unity, the latent segmentation model specifies the (fixed) variance of the unobserved effects at the upper level(s) (ie λ^2 and γ^2) as a function of the characteristics of each individual (in principle one could include the attributes of the alternatives) with data collection variables included to 'cleanse' the segments of bias due to noise in information gathering. This is equivalent to a fixed effects HEV model and is referred to as a *latent segmentation partitioned logit* model (Swait 1994, Louviere et al in press).

Random parameter logit (RPL) or mixed logit (ML) model

The utility expression is the same as that for a standard MNL model except that the analyst may nominate one or more taste weights (including alternative-specific constants) to be treated as random parameters with the variance estimated together with the mean. The layering of selected random parameters can take a number of predefined functional forms, typically assumed to be normally or lognormally distributed. The normal form is $\beta_{qk} \sim N(\beta_k + \nu_{qk})$ where β_k is the mean response sensitivity across all observations for attribute *k*, and ν_{qk} represents random taste variation of individual q around the mean. The lognormal form is often used if the response parameter needs to be a specific sign: $\beta_{qk} \sim \pm \exp(\beta_k + \nu_{qk})$.

This form has important behavioural implications. The presence of ν_{qk} terms as a representation of random tastes of individual q invariant across the choice set, can induce a correlation among the utility of different alternatives (Bhat 1997, McFadden and Train 1996). It is the mixture of an EV1 distribution for the overall utility expression and embedded normality for the distribution of the taste weights across a sample which has led to the phrase 'mixed logit' (Train 1997, 1999). Specifically, by treating the deviation around the mean taste weight as a component of the random component such that we have $\nu_{qk}x + \varepsilon_i$, the RPL model has been interpreted as an error-components model, where the first component can take on any distributional assumption and the second component is assumed to be EV1. One can also choose to treat the random effects, $\nu_{qk}x$, as different across the alternatives but independent (ie different standard deviations); or as different across alternatives and inter-alternative correlated.

This engenders a relatively free utility structure such that IIA is relaxed despite the presence of the IID assumption for the random components, ε_i, of the alternatives. That is, the RPL model disentangles IIA from IID and enables the analyst to estimate models that account for cross-correlation among the alternatives. When the random taste weights are all zero, the exact MNL model is produced. Applications of the RPL/mixed logit model are given in Bhat (1997), Revelt and Train (1996), Brownstone and Train (1999) and McFadden and Train (1996). Bhat (1997) has superimposed random response heterogeneity over the systematic response heterogeneity by including parameterised covariates (Z_{qk}) in the function: $\beta_{qk} \sim \pm \exp(\beta_k + \gamma_k Z_{qk} + \nu_{qk})$.

Multinomial probit (MNP)

For MNP, a choice probability P_r with a choice set size R is calculated by multidimensional integration associated with e, as given in (14).

$$P_r = \int_{e=-\infty}^{e_r+V_r-V_l} \ldots \int_{e_r=-\infty}^{\infty} \ldots \int_{e_r=-\infty}^{e_r+V_r-V_R} f(e)\mathrm{d}e_R \ldots \mathrm{d}e_1 \qquad (14)$$

The density function is described by (15).

$$f(e) = (2p)^{-\frac{R}{2}} | \quad |^{-\frac{1}{2}} \exp[-\frac{1}{2}e \quad ^{-1}e^T] \qquad (15)$$

The covariance matrix is shown as (16).

$$\Sigma = \begin{pmatrix} s_1^2 & s_{12} & \cdots & s_{1R} \\ s_{12} & s_2^2 & & \vdots \\ \vdots & & \ddots & \\ s_{1R} & \cdots & & s_R^2 \end{pmatrix} \qquad (16)$$

We omit notation for an individual for simplicity. Elements of the symmetric covariance matrix Σ, usually defined as parameters, are estimated simultaneously with parameters of the utility function V_r. A set of the estimated elements in the matrix is constant for the population. Estimation of this model requires the analyst to select the specific form of the error covariance matrix and to select the off-diagonal correlations that should be non-zero. The non-zero covariances can be constrained as equal across specific pairs of alternatives; however, this requires parsimonious judgement to be exercised since the addition of a free covariance adds substantial complexity in estimation. Each alternative also has a standard deviation for each of the diagonal elements, which requires setting at least one of them to equal 1.0 for identification; experimentation with behaviourally reasonable differences should be undertaken with care. Analysts should experiment with a number of optimisation algorithms, together with varying tolerances and steps in function evaluation. In recent years there have been substantial improvements in numerical methods for simulated maximum likelihood estimation. We turn to the most promising method – Halton sequences.

Halton sequences

The multinomial probit and random parameter/mixed logit models are estimated using the Halton draws method (Bhat 1999), an alternative to the random draws approach using the simulated maximum likelihood (SML) method. Random draws are used herein to estimate CovHet and HEV. Numerous procedures have been proposed for taking *intelligent* draws from a distribution rather than random ones (e.g., Sloan and Wozniakowski, 1998; Morokoff and Caflisch, 1995.) Rather than using psuedo-random sequences for the discrete points in a distribution, a quasi-Monte Carlo approach uses non-random and more uniformly distributed sequences within the domain of integration (Bhat 1999, 3). Thus the coverage of the random utility space is more representative.

The procedures offer the potential to reduce the number of draws that are needed for estimation of RPL/ML and MNP models, thereby reducing run times, and/or to reduce the simulation error that is associated with a given number of draws. Bhat (1999)[3] and Train (1999) have investigated Halton sequences for mixed logit estimation and found their use to be vastly superior to random draws. In particular, they found that the simulation error in the estimated parameters was lower using 100 Halton numbers than 1000 random numbers. In fact, with 125 Halton draws, they both found the simulation error to be half as large as with 1000 random draws and smaller than with 2000 random draws. The estimation procedure is much faster (often 10 time faster). We have investigated Halton sequences involving draws of 10, 25, 50, 100, 150 and 200 and compared the findings with random draws. In all models of the RPL and MNP investigated we conclude that a small number of draws (as low as 50) produces model fits and values of travel time savings that are almost indistinguishable (and at worse

[3] Bhat (in press) also uses Halton draws in mixed logit estimation but does not describe his tests against random draws.

very similar – see footnote 4 for MNP). This is a phenomenal development in the estimation of complex choice models.

Design Of The Stated Choice Experiment

The central feature of the empirical strategy is a stated choice experiment. The design is based on two unlabelled alternatives each defined by six attributes each of four levels (ie 4^{12}): free flow travel time, slowed down travel time, stop/start travel time, uncertainty of travel time, running cost and toll charges. Except for toll charges, the levels are *proportions* relative to those associated with a current trip identified prior to the application of the SC experiment:

Free flow travel time:	-0.25, -0.125, 0.125, 0.25
Slowed down travel time:	-0.5, -0.25, 0.25, 0.5
Stop/Start travel time:	-0.5, -0.25, 0.25, 0.5
Uncertainty of travel time:	-0.5, -0.25, 0.25, 0.5
Car running cost:	-0.25, -0.125, 0.125, 0.25
Toll charges ($):	varies depending on trip segment (up to $30 for long trip)

Including the current (ie revealed preference (RP)) alternative, described by the exact same six attributes as the two SC alternatives, the design starts with six columns of zeros for the last trip attributes followed by six attributes for alternative A and then six attributes for alternative B. For example: 0, 0, 0, 0, 0, 0 -0.125, -0.5, 0.25, -0.25, 0.25, 1 0.125, 0.25, -0.25, 0.5, -0.25, 1. The six attributes for alternative A are orthogonal to the six columns for alternative B, allowing for the estimation of models with complex structures for the random components of the utility expression associated with each of the alternatives (Louviere, Hensher and Swait in press). The levels of the attributes for both SC alternatives were rotated to ensure that neither A nor B would dominate the RP trip, and to ensure that A and B would not dominate each other. For example, if free flow travel time for A was better than free flow travel time for the RP trip, then we structured the design so that at least one among the five remaining attributes would be worse for alternative A relative to the RP trip; and likewise for the other potential situations of domination.

The fractional factorial design has 64 rows. We allocated four blocks of 16 "randomly" to each respondent, defining block 1 as the first 16 rows of the design, block 2 the second set of 16 etc. Formally, we draw block b from blocks 1, 2, 3 and 4 and assign block b to respondent 1, block [((b-1) mod 4) +1] to respondent 2, block [(b mod 4) +1] to respondent 3, block [((b+1) mod 4) +1] to respondent 4. We then go to block 1 for the next set of four respondents. For example, if the first respondent faces block 3 of the design, the next three respondents will receive blocks 4, 1 and 2 in that order. Once the whole design has been allocated we again draw a number from 1 to 4 and repeat the block sequence. The advantage is that if the number of respondents interviewed by each interviewer is a multiple of four we will have exactly the same number of respondents in each block. If not, we do not expect to be far from symmetrical representation of each block, a condition for complete orthogonality in model estimation.

The assignment of levels to each SC attribute conditional on the RP levels is straightforward. However, if the RP trip had a zero level for an attribute (which is possible for one or more components of travel time), we introduced rules of variation. The rules are as follows:

Free Flow for alternatives A and B = free flow for RP trip * (1+level); but if "Free Flow" for RP trip is zero then free flow for alternatives A and B = 0.1 * (Total time for RP trip) * (1+level). Slowed down time for alternatives A and B = 0.9*(Slowed time for RP trip) * (1+level), and stop/start time for alternatives A and B = 0.9*(Stop/Start time for RP trip) * (1+level). Otherwise, Slowed Down time for alternatives A and B = Slowed down time for RP trip * (1+level) and Stop/Start time for alternatives A and B= Stop/Start time for RP trip * (1+level).

If slowed down time for the RP trip is zero then slowed down time for alternatives A and B= 0.1 * (Free Flow of RP trip) * (1+level). If Stop/Start time for the RP trip is zero then stop/start time for alternatives A and B = 0.1 * (Free Flow for RP trip) * (1+level). Uncertainty for alternatives A and B = uncertainty for RP trip (1+level). If uncertainty for the RP trip is zero then uncertainty for alternatives A and B= 0.1 * (Total time for RP trip) * (1+level). Running Cost for the RP trip is taken as 10 cents per kilometre, and running cost for alternatives A and B= running cost for RP trip * (1+level). Finally, the toll charges are defined as follows:

urban trips levels: $0, $2, $4, $6
interurban trips lasting up to 90mins: $0, $3, $6, $9
interurban trips lasting between 90 and 180 mins: $0, $5, $10, $15
interurban trips lasting more than 180mins: $0, $10, $20, $30

An SC screen is shown in Figure 1. The data on the RP trip is identified from earlier questions and imported into the SC screen together with the attribute levels offered by alternatives A and B in accordance with the rules presented above. TIMEX99 automates the complete data collection process, accumulating respondent answers together with the design attribute levels into an MS-Access data base ready for choice model estimation.

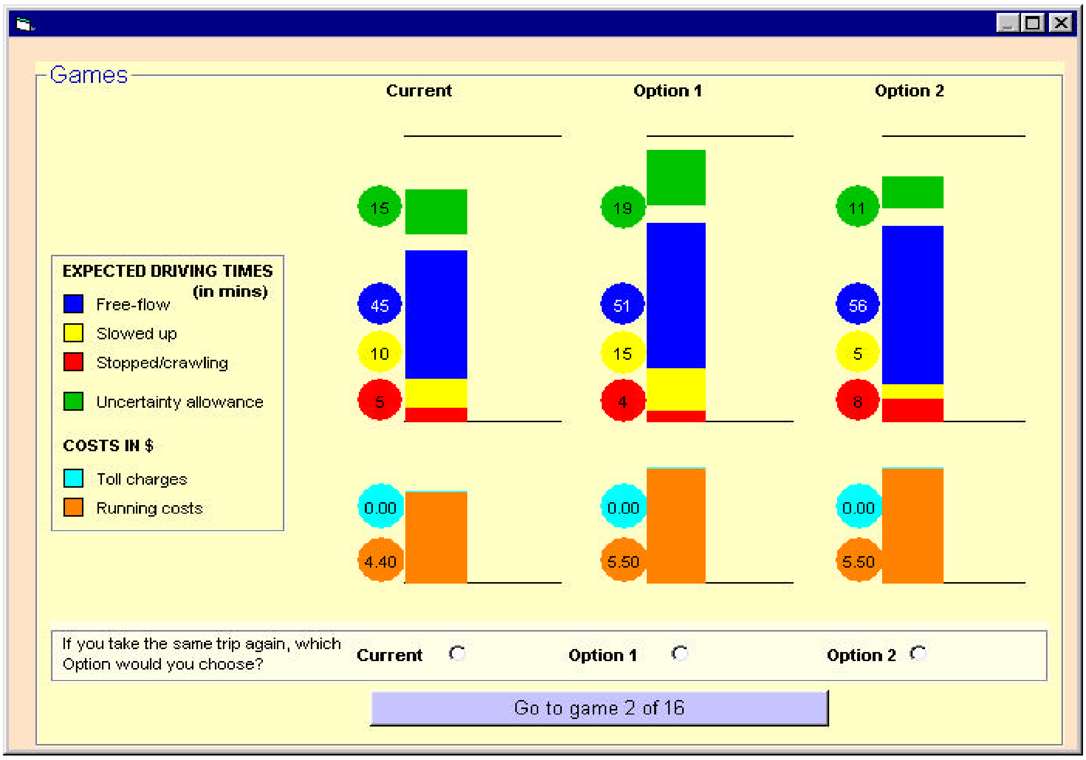


Figure 1. An example of a stated choice screen

Empirical Analysis

Descriptive statistics for each urban segment are presented in Table 1. The mean for each design attribute is based on the current trip levels and the variations around this level as produced by the experiment design. The most interesting evidence relates to the composition of travel time, especially the proportion of the trip time that is free flow in contrast to the current time which includes all sources of delay. The italicised columns in Table 1 provide the evidence on the contribution of delays to travel time. As expected, commuters incur the greatest percentage of delay time (31.7%) in contrast to 23.9% for local non-commuters. In absolute terms however the average delay of 6.6 minutes for commuters contrasts with 4.5 minutes for non-commuters, a small difference of 2.1 minutes. The average trip length is almost identical for commuters and non-commuters (ie 16.2 and 16.6 minutes respectively) although the trip length distribution is longer for commuters (a standard deviation of 22.2 minutes) compared to non-commuters (a standard deviation of 13.4 minutes). The personal income of commuters is higher than that for non-commuters, due to the incidence of over 50% of the non-commuter segment being non-workers.

Table 1 Summary Descriptive Statistics for each Segment (mean with standard deviation in brackets)

Attributes	Local Commuter MNL	Local Non Commuter MNL
Free flow time (mins)	11.2 (6.9)	14.6 (9.9)
Slowed down time (mins)	5.4 (5.8)	4.9 (5.6)
Stop/start time (mins)	4.0 (4.7)	2.6 (3.0)
Uncertainty (mins)	8.2 (6.8)	9.3 (7.3)
Running cost ($)	1.5 (1.4)	1.7 (1.6)
Toll Charges ($)	2.0 (2.3)	2.0 (2.3)
No adults	1.4 (2.4)	1.9 (3.3)
No children	.09 (.34)	0.6 (1.0)
Time last trip (mins)	*20.8 (16.6)*	*20.9 (10.9)*
Time last trip if no congestion (mins)	*14.2 (14.6)*	*15.9 (9.6)*
Percent of trip time that is delayed time (%)	*31.7*	*23.9*
Current trip length (kms)	16.2 (22.2)	16.6 (13.4)
Fuel paid by driver (%)	91.6	88.6
Age of driver (years)	39.6 (14.1)	46.9 (17.2)
Personal income ($pa)	31798 (20619)	24128 (19490)
Full time work (%)	60.9	24.9
Part time work (%)	25.2	17.1
Casual work (%)	8.6	9.2
Sample Size	2427	2437

Final choice models

A series of models were estimated to identify the role, in the urban commuter and non-commuter markets, of each trip attribute in the SC experiment for the choice between the current car trip and two other trip scenarios on offer. All models are unordered and unlabelled in respect of the utility expressions defining the current trip (CURR) and the two experimental design alternatives (ALTA and ALTB). An unlabelled model specification treats the options as alternative descriptors of a bundle of attribute levels with no labelling of the specific alternatives. That is, the notion of a labelled route called ALTA or ALTB or even CURR is uninformative in estimation since what defines the trading between the options is the set of attributes in the design. All attributes are route abstract and as such are treated as generic attributes in model estimation. We specifically structured the survey to avoid a requirement for route switching. The objective was to evaluate alternative attribute bundles for travelling between predetermined locations by the existing route and time of day.

The final commuter models are summarised in Table 2 and the non-commuter models in Table 3. The overall goodness of fit of all models is impressive. In the current paper we will concentrate on those aspects of the models that are especially relevant in the derivation of the values of travel time savings. We have estimated three model forms. Model 1 treats all time and cost as homogenous in its parameters and as such the VTTS is an unweighted average across the entire composition of time and cost. Model 2 preserves the homogeneity assumption for cost but recognises the difference in marginal utility for each time component. Four VTTS will be derived respectively for free flow time, slowed down time, stop/start time and trip arrival time contingency (ie uncertainty). Model 3 permits unique parameter estimates for the components of cost and time. Eight VTTS are derived, four for the time components based on marginal utility of running cost and four based on the marginal utility of toll charge.

Although economic theory prescribes one marginal utility for cost regardless of the level and units (no money illusion), the implicit assumption is that units of cost are free from lumpiness or indivisibility constraints. Individuals however do impose nonlinearity on the preference function for dollar commitments that is in large measure a function of the mechanism through which costs are expended. Running costs described in the stated choice experiment as fuel are a financial commitment at the time of refuelling and which has high perceptual discounting in terms of its influence at the time of car use. In contrast a toll is an outlay that is normally 'physically' transferred at the point of car use from the driver to the toll booth attendant. We hypothesise that VTTS will be higher when trading time with the toll than with the running costs. This is confirmed by the evidence below. The perception of a lumpy sum is strong. However, as automatic and electronic tolling becomes more widespread as it is in some countries (but not New Zealand), tolls will take on the same perceptual characteristics as fuel; that is they will be heavily discounted in their impact.

Beginning with the MNL model, all parameter estimates are highly statistically significant (t-values greater than 5.0), facilitating robust VTTS for each time component. In addition the directional relativities between free flow time, slowed down time and stop/start time are as expected, with the marginal disutility increasing for the less attractive time component (ie stop/start). For example, in models 2 and 3 the ratio of free flow time to slowed down time is 1.09-1.12 for commuters and 2.71-2.78 for non-commuters; the ratio of free flow time to stop/start time is 2.23-2.24 for commuters and 3.39-4.7 for non-commuters. It is informative to note that the free flow to slowed down time ratio is slightly greater than 1.0 for commuters but more than double for stop/start time, suggesting that commuters have adjusted to patterns of what we might describe as constant (above free) flow time such that the marginal disutility of such time approximates that of free flow time. In contrast however, stop/start time is a source of substantially higher marginal disutility. From a policy perspective this suggests greater effort in eliminating sources of 'erratic' travel such as (unpredictable) incidents. The VTTS associated with stop/start time appears to be the appropriate value to use in the evaluation of incident management schemes.

The relativity between the time components is preserved across all five specifications of the unobserved effects subject to the non-comparability where a time component is statistically non-significant (as it is in some of the ML/RPL models for free flow time for commuters and stop/start time for non-commuters).

The HEV model introduces two additional (scale) parameters to represent the inverse of the standard deviation of the random components of each utility expression. Setting the scale to unity for Alt B, we have scale parameters for the current trip and Alt A of 0.62-0.65 and 0.80-0.81 respectively for commuters across models 1-3. The equivalent scale parameters for non-commuters are 0.61-0.65 and 0.94-0.96. The degree of closeness between Alt A and the normalised Alt B compared to the current trip and Alt B is expected and is encouraging, suggesting that there may be some other influences that we have not explicitly accounted for that have a differential influence on choosing Alt A or Alt B rather than staying with the current trip attribute levels. The covariate heterogeneity model may help us here. Looking ahead to the CovHet models where we have partitioned the model into two latent segments – one for the current trip and the other for alternatives A and B, we find that the inclusive value parameters (equivalent to the inverse of the square of the scale parameters) are very similar. In particular, for commuters the range for each of models 1-3 is respectively 1.35-1.49, 1.37-1.49, and

1.39-1.51. For non-commuters the range is 0.432-0.485, 0.447-0.490 and 0.422-0.458. The three covariates that have been introduced to account for differences in scale are personal income, age of driver and full time worker status (yes, no). Thus we might conclude that the differences in scale identified in the HEV model are explained by three socioeconomic characteristics of the car driver. The comparison of the two specifications of HEV models (random and fixed effects) has enabled us to identify observable influences on choice that otherwise would have remained unobserved influences in the random effects HEV model.

Comparing MNL, HEV, CovHet and MNP VTTS in Tables 4 and 5 we note, with rare exception, that VTTS increases as we move from MNL to HEV to MNP to CovHet. A closer look at the directional changes in VTTS suggests that the source of the cost parameter has the greatest bearing on the findings. The use of the running cost parameter tends to flatten out or lower the VTTS as we move from MNL to HEV to MNP to CovHet; in contrast the opposite occurs when the toll charge parameter is used. If we were comparing total time (model 1), which is the model form most commonly used in other studies of car travel, we would conclude that VTTS has been underestimated when obtained from an MNL model. However, when we decompose travel time we have a mixed set of findings. The underestimation appears to hold for all time components for commuter travel when total cost or toll cost is the base cost, but the opposite appears to be the case when running cost is the base cost.

The introduction of the RPL/mixed logit model produces some startling contrasts. Although we allowed for potential correlation between the attributes we rejected the null hypothesis of correlation. Without exception, all standard deviations of the attribute parameters are statistically non-significant, thus the mean estimates are strictly homogeneous. If we had found some statistical significance we could have established whether the orthogonality condition between the mean estimates of each attribute parameter is preserved in the standard deviations of the attribute parameters.

We have introduced choice invariant characteristics to induce individual heterogeneity in the means of the randomly distributed parameters associated with each trip attribute. We report only the statistically significant effects (with t-values greater than 1.6). All parameters are assumed to be normally distributed. For example, in the commuter model, we find that there is a strong positive age effect for total time, total cost and the components of cost. Thus we can conclude that the marginal utility of total time, total cost and the cost components decreases as the age of the driver increases. In commuter model 2 we find that slow time is a positive function of driver age, and thus the marginal utility of slow time decreases as the driver ages. The full time worker effect also has an influence on the distribution of parameters for total cost and toll charges implying that the marginal disutility of cost or toll is lower for a full time worker in contrast to other worker status (ie part time and casual). This makes sense. Overall we find strong age and full time work status effects for commuters and non-commuters as explanations of heterogeneity in the means of the randomly distributed attribute parameters. Personal income was not statistically significant. This was also confirmed in the CovHet model for commuters but not for non-commuters, although in the case of non-commuters we had a swapping of significance between personal income and full time work status in CovHet suggesting a strong link between the two socioeconomic characteristics.

The statistically significant VTTS in the mixed logit model are within the HEV/CovHet range for total commuter time but substantially higher for total non-commuter time. The latter may be the results of statistical significance that is still good (ie t-values of –2.9 and –4.6) but noticeably less significant than for all the other models (ie –7.4 and –17.7). An assessment of all statistically significant VTTS across all mixed logit models suggests higher VTTS compared to MNL where cost is total cost or toll charges and lower VTTS when cost is running cost (Table 4). For non-commuters the VTTS are substantially higher for all cost contexts for all time components (Table 5). We suggest caution in the comparison between the mixed logit model results and the other models until we have more confidence in a reason for such noticeable contrasts.

Table 2. Final Urban Models Used to Obtain Empirical Estimates of Values of Travel Time Savings: Local Commuters. All travel times are in minutes and costs are in dollars

Attributes	Local Commuter: MNL	Local Commuter: HEV	Local Commuter: CovHet	Local Commuter: RPL/ML Corr	Local Commuter: MNP
Model 1:					
Total time	-.1306 (13.2)	-.1327 (-12.3)	-.1312 (-11.5)	-.2118 (-5.5)	-.1032 (-13.1)
Total cost	-.7157 (-30.7)	-.7123 (-25.9)	-.5971 (-16.6)	-.9282 (-15.7)	-.5451 (-25.3)
Scale parameters:					
Current		.623 (7.5)			
Alt A		.813 (20.6)			
Inclusive Values:					
Current			1.35 (8.0)		
Alt AB			1.49 (8.1)		
Covariates in inclusive values:					
Personal income			.0025 (1.5)		
Ages			-.0049 (-2.1)		
Fullt time work dummy			-.318 (-4.2)		
Heterogeneity in mean					
Total time: age				.00230 (2.6)	
Total time: full time work					
Total cost: income					
Total cost: age				.00392 (3.0)	
Total cost: full time work				.1052 (2.5)	
Std Dev. of beta distn					
Total time				.00062(.045)	
Total cost				.0024(.100)	
Std Dev of normal distn:					
Alt A					1.286 (17.5)
Corr in normal distn:					
Alt A, Alt B					.01755 (.13)
Pseudo-r^2	.434	.426	.308	.434	.421
Log-likelihood	-1508.6	-1529.0	-1480.1	-1477.3	-1513.6
Model 2:					
Free flow time	-.09597 (-5.3)	-.1080 (-4.8)	-.1055 (-5.3)	-.1298 (-1.6) ns	-.0777 (-5.1)
Slowed down time	-.10754 (-7.3)	-.0999 (-6.3)	-.1073 (-6.9)	-.2005 (-3.6)	-.0813 (-7.2)
Stop/start time	-.21538 (-10.7)	-.2239 (-8.8)	-.2068 (-8.8)	-.3702 (-4.3)	-.1727 (-9.8)
Uncertainty	-.05972 (-5.2)	-.0551 (-4.0)	-.05772 (-4.8)	-.0562 (-1.2) ns	-.0441 (-4.6)
Total cost	-.72787 (-30.5)	-.7148 (-24.7)	-.6087 (-16.2)	-.9669 (-15.9)	-.5491 (-25.3)
Scale parameters:					
Current		.65 (7.0)			
Alt A		.80 (19.5)			
Inclusive Values:					
Current			1.37 (7.9)		
Alt AB			1.49 (8.0)		
Covariates in inclusive values:					
Personal income			.00255 (1.6)		
Ages			-.00465 (-2.1)		
Fullt time work dummy			-.3170 (-4.3)		
*Heterogeneity in mean * (only significant betas)*					
Slow time: full time worker					
Slow time: age				.00248 (2.0)	
Uncert: income				-.00109 (-1.7)	
Uncert: full time work				.0047 (1.6)	

Table 2 continued

Total cost: age				.00465 (3.5)	
Total cost: full time work				.1301 (3.0)	
Std Dev. of beta distn					
Free flow time				.00104 (.04)	
Slow down time				.00086 (.05)	
Stop/start time				.00553 (.21)	
Uncertainty				.00275 (.18)	
Total cost				.00172 (.09)	
Std Dev of normal distn:					
Alt A					1.297 (18.8)
Corr in normal distn:					
Alt A, Alt B					.0575 (.44)
Pseudo-r^2	.443	.434	.319	.441	.429
Log-likelihood	-1483.3	-1508.3	-1456.9	-1450.5	-1489.3
Model 3:					
Free flow time	-.09677 (-5.4)	-.1082 (-4.8)	-.1078 (-5.4)	-.1303 (-1.6) ns	-.0794 (-5.2)
Slowed down time	-.10598 (-7.2)	-.0988 (-6.3)	-.1023 (-6.6)	-.1778 (-3.2)	-.0811 (-7.2)
Stop/start time	-.21671 (-10.7)	-.2288 (-8.8)	-.2093 (-8.8)	-.3872 (-4.6)	-.1745 (-9.9)
Uncertainty	-.06003 (-5.2)	-.0559 (-4.1)	-.0582 (-4.8)	-.0642 (-1.4)	-.0436 (-4.5)
Running cost	-.88648 (-7.3)	.9579 (-6.9)	-.9981 (-7.6)	-2.774 (-4.9)	-.6605 (-7.4)
Tolls	-.72621 (-30.4)	-.7146 (-24.7)	-.5981 (16.0)	-.9609 (-15.4)	-.5510 (-25.3)
Scale parameters:					
Current		.638 (7.1)			
Alt A		.805 (19.4)			
Inclusive Values:					
Current			1.39 (7.9)		
Alt AB			1.51 (8.0)		
Covariates in inclusive values:					
Personal income			.00263 (1.7)		
Ages			-.0051 (-2.3)		
Fullt time work dummy			-.3212 (-4.4)		
*Heterogeneity in mean * (only significant betas)*					
Slow time: full time worker					
Slow time: age					
Stop/start time: age				0.0021 (1.7)	
Uncert: income				-.00111 (-1.7)	
Uncet: full time worker				.04759 (1.6)	
Running cost: age				.0347 (3.1)	
Toll: age				.0045 (3.3)	
Toll: full time work				.1312 (3.0)	
Std Dev. of beta distn					
Free flow time				.0008 (.03)	
Slow down time				.00032 (.02)	
Stop/start time				.00027 (.01)	
Uncertainty				.00014 (.01)	
Running cost				.0120 (.10)	
Toll Charges				.00123 (.06)	
Std Dev of normal distn:					
Alt A					1.293 (17.3)
Corr in normal distn:					
Alt A, Alt B					.0168 (.12)
Pseudo-r^2	.443	.434	.320	.445	.429
Log-likelihood	-1482.4	-1506.6	-1482.4	-1443.8	-1490.48

Table 3.. Final Urban Models Used to Obtain Empirical Estimates of Values of Travel Time Savings: Local Non-Commuters. All travel times are in minutes and costs are in dollars

Attributes	Local Non Commuter: MNL	Local Non Commuter: HEV	Local Non Commuter: CovHet	Local Non Commuter: RPL/ML Corr	Local Non Commuter: MNP
Model 1:					
Total time	-.0686 (-7.6)	-.0624 (-6.5)	-.0667 (-7.4)	-.0562 (-2.3)	-.0481 (-7.3)
Total cost	-.6872 (-30.5)	-.6533 (-24.5)	-.629 (-17.7)	-.2104 (-4.0)	-.4979 (-27.4)
Scale parameters:					
Current		0.61 (7.6)			
Alt A		0.94 (19.6)			
Inclusive Values:					
Current			0.432 (6.5)		
Alt AB			0.485 (6.6)		
Covariates in inclusive values:					
Personal income			-.044 (-2.0)		
Ages			.0185 (7.1)		
Fullt time work dummy			-.0894 (-.9)		
Heterogeneity in mean					
Total time: income					
Total time: age					
Total time: full time work					
Total cost: income					
Total cost: age				-.00118 (-9.0)	
Total cost: full time work					
Std Dev. of beta distn					
Total time				.00015 (.01)	
Total cost				.00082 (.03)	
Std Dev of normal distn:					
Alt A					1.079 (15.4)
Corr in normal distn:					
Alt A, Alt B					-.0281 (-.2)
Pseudo-r^2	.413	.407	.282	.427	.401
Log-likelihood	-1571.0	-1587.3	-1531.6	-1525.6	-1566.2
Model 2:					
Free flow time	-.03113 (-2.3)	-.0307 (-2.2)	-.0347 (-2.7)	-.0494 (-1.4) ns	-.0221 (-2.2)
Slowed down time	-.08446 (-5.4)	-.0672 (-4.4)	-.0792 (-5.3)	-.1289 (-2.2)	-.0516 (-4.7)
Stop/start time	-.13667 (-5.7)	-.1311 (-4.9)	-.1305 (-4.8)	.0591 (.83) ns	-.1111 (-5.9)
Uncertainty	-.04199 (-4.0)	-.0359 (-3.2)	-.0399 (-4.1)	-.0320 (-.99) ns	-.0303 (-3.8)
Total cost	-.67917 (-29.8)	-.6314 (-23.8)	-.630 (-17.4)	-.2385(-4.3)	-.4899 (-27.4)
Scale parameters					
Current		.651 (7.2)			
Alt A		.954 (19.9)			
Inclusive Values:					
Current			.447 (6.6)		
Alt AB			.490 (6.7)		
Covariates in inclusive values:					
Personal income			-.0044(-2.1)		
Ages			.0183 (7.1)		
Fullt time work dummy			-.0807 (-.8)		
*Heterogeneity in mean * (only significant betas)*					
Slow time: full time worker				.1429 (2.7)	
Stop/start time: age				0.00494 (-3.2)	
Total cost: age				-.01026 (-8.09)	

Table 3 continued

Total cost: full time work				.0835 (1.53)	
Std Dev. of beta distn					
Free flow time				.00227 (.13)	
Slow down time				.00294(.16)	
Stop/start time				.00295 (.10)	
Uncertainty				.00104 (.09)	
Total cost				.00179 (.09)	
Std Dev of normal distn:					
Alt A					1.069 (15.1)
Corr in normal distn:					
Alt A, Alt B					-.0481 (-.31)
Pseudo-r^2	.419	.411	.288	.434	.406
Log-likelihood	-1554.4	-1575.9	-1518.3	-1498.7	-1580.9
Model 3:					
Free flow time	-.03134 (-2.3)	-.0294 (-2.1)	-.0379 (-2.8)	-.0522 (-1.5) ns	-.0211 (-2.1)
Slowed down time	-.08674 (-5.4)	-.0657 (-4.4)	-.0786 (-5.2)	-.1347 (-2.4)	-.0501 (-4.6)
Stop/start time	-.14701 (-6.1)	-.1469 (-5.3)	-.1405 (-4.9)	.0628 (.9) ns	-.1201 (-6.4)
Uncertainty	-.04242 (-4.1)	-.0375 (-3.2)	-.0409 (-4.1)	-.0310(-.98) ns	-.0308 (-3.9)
Running cost	-1.1101 (-10.0)	-1.126 (-9.7)	-1.28 (-10.2)	-.3978 (-1.2) ns	-.8487 (-10.7)
Tolls	-.67487 (-29.8)	-.6293 (-24.3)	-.624 (-17.3)	-.2388 (-4.4)	-.4867 (-27.3)
Scale parameters					
Current		0.62 (7.9)			
Alt A		0.96 (19.5)			
Inclusive Values:					
Current			.422 (6.7)		
Alt AB			.458 (6.8)		
Covariates in inclusive values:					
Personal income			-.0407 (-1.9)		
Ages			.0188 (7.3)		
Fullt time work dummy			-.057 (-.6)		
*Heterogeneity in mean * (only significant betas)*					
Slow time: full time worker				.1442(2.7)	
Stop/start time: age				-.0053 (-3.4)	
Running cost: age				-.01741 (-2.1)	
Toll: age				-.0101 (-7.9)	
T\oll: full time worker				.08662 (1.6)	
Std Dev. of beta distn					
Free flow time				.0014 (.08)	
Slow down time				.0029 (.17)	
Stop/start time				.0009 (.04)	
Uncertainty				.0006 (.05)	
Running cost				.0112 (.10)	
Toll Charges				.0007 (.04)	
Std Dev of normal distn:					
Alt A					1.062 (15.0)
Corr in normal distn:					
Alt A, Alt B					.0447 (-.3)
Pseudo-r^2	.422	.414	.294	.438	.409
Log-likelihood	-1546.2	-1566.5	-1504.4	-1488.8	-1571.6

Table 4 Values of Travel Time Savings for each Segment ($ per person hour, NZ$99): Local Commuters
awr = average wage rate

Attributes	Local Commuter: MNL	Local Commuter: HEV	Local Commuter: CovHet	Local Commuter: RPL/ML	Local Commuter: MNP
Model 1:					
Total time	10.96	11.18	13.20	13.69	11.36
As % awr	*68.9*	*70.3*	*83.0*	*86.1*	*71.4*
Model 2:					
Free flow time	7.92	9.07	10.4	ns	8.49
Slowed down time	8.86	8.38	10.6	12.4	8.89
Stop/start time	17.75	18.79	20.4	22.9	18.87
Uncertainty	4.92	4.63	5.69	ns	4.82
Model 3 for running cost:					
Free flow time	6.55	6.78	6.48	ns	7.22
Slowed down time	7.17	6.19	6.15	3.84	7.37
Stop/start time	14.6	14.3	12.6	8.37	15.86
Uncertainty	4.06	3.50	3.50	ns	3.96
Model 3 tolls:					
Free flow time	7.99	9.08	10.8	ns	8.65
Slowed down time	8.75	8.30	10.3	11.1	8.83
Stop/start time	17.9	19.2	21.0	24.2	19.00
Uncertainty	4.96	4.69	5.84	ns	4.75

Table 5 Values of Travel Time Savings for each Segment ($ per person hour, NZ$99): Local Non-Commuters

Attributes	Local Non Commuter: MNL	Local Non Commuter: HEV	Local Non Commuter: CovHet	Local Non Commuter: RPL/ML	Local Non Commuter: MNP
Model 1:					
Total time	5.99	5.73	6.36	16.03	5.81
As % awr	*49.6*	*47.5*	*52.7*	*133*	*48.2*
Model 2:					
Free flow time	2.75	2.92	3.30	ns	2.67
Slowed down time	7.46	6.38	7.54	32.2	6.32
Stop/start time	12.07	12.5	12.42	ns	13.62
Uncertainty	3.70	3.41	3.8	ns	3.72
Model 3 for running cost:					
Free flow time	1.69	1.57	1.72	ns	1.49
Slowed down time	4.69	3.50	3.66	ns	3.55
Stop/start time	7.95	7.83	6.55	ns	8.50
Uncertainty	2.29	1.98	1.91	ns	2.18
Model 3 tolls:					
Free flow time	2.78	2.80	3.57	ns	2.60
Slowed down time	7.71	6.26	7.59	33.8	6.18
Stop/start time	13.07	14.0	13.56	ns	14.82
Uncertainty	3.77	3.57	3.95	ns	3.80

6. Conclusion

This study has focused on the impact of alternative assumptions on the random components of the underlying utility expressions representing the preferences of individual car drivers for alternative bundles of trip attributes[4]. We have distinguished free flow time, slowed down time and stop/start time. In addition we have accounted for the contingency time that a traveller includes in the face of uncertainty in respect of arrival time at a destination. Trip cost is disaggregated into running costs and toll charges in order to recognise the broadening range of monetary costs that impact directly on a trip.

The findings are rich in evidence throughout a number of market segments. The major findings for each segment are summarised in Table 6, with the ranges representing the alternative cost base (ie running cost, toll cost and total cost). A comparison with Transfund New Zealand's interim 1997/98 Evaluation Procedures for Alternatives to Roading First Edition 1 June 1997 lists in Appendix A4 a vehicle occupant *resource* VTTS for non-work travel purpose for car driver of NZ$97 6.50. Non-work includes commuting. This estimate is directly comparable to the weighted average of $10.96 and $5.99 in Tables 4 and 5, where the weights are the mix of commuting and non-commuting local trips.

[4] We estimated models for Halton draws of 10, 25, 50, 100, 150 and 200 for local commuters and found very close equivalence as summarised in the Table below. All VTTS are in $NZ per person hour. We have used 50 draws in the models reported in the text.

Halton draws:	10	25	50	100	150	200
Running cost:						
Free flow time	7.21	7.11	7.22	7.13	7.15	7.18
Slowed down time	7.45	7.31	7.37	7.32	7.32	7.33
Stop/start time	15.77	15.81	15.86	15.81	15.79	15.79
uncertainty	3.97	3.99	3.96	3.97	3.98	3.96
Toll cost:						
Free flow time	8.56	8.54	8.65	8.58	8.59	8.64
Slowed down time	8.85	8.79	8.83	8.81	9.24	8.82
Stop/start time	18.73	19.00	19.00	19.02	18.98	19.07
uncertainty	4.71	4.80	4.75	4.78	4.79	4.76
Log-likelihood	-1494.053	-1492.123	-.1490.48	-1490.829	-1492.17	-1491.216

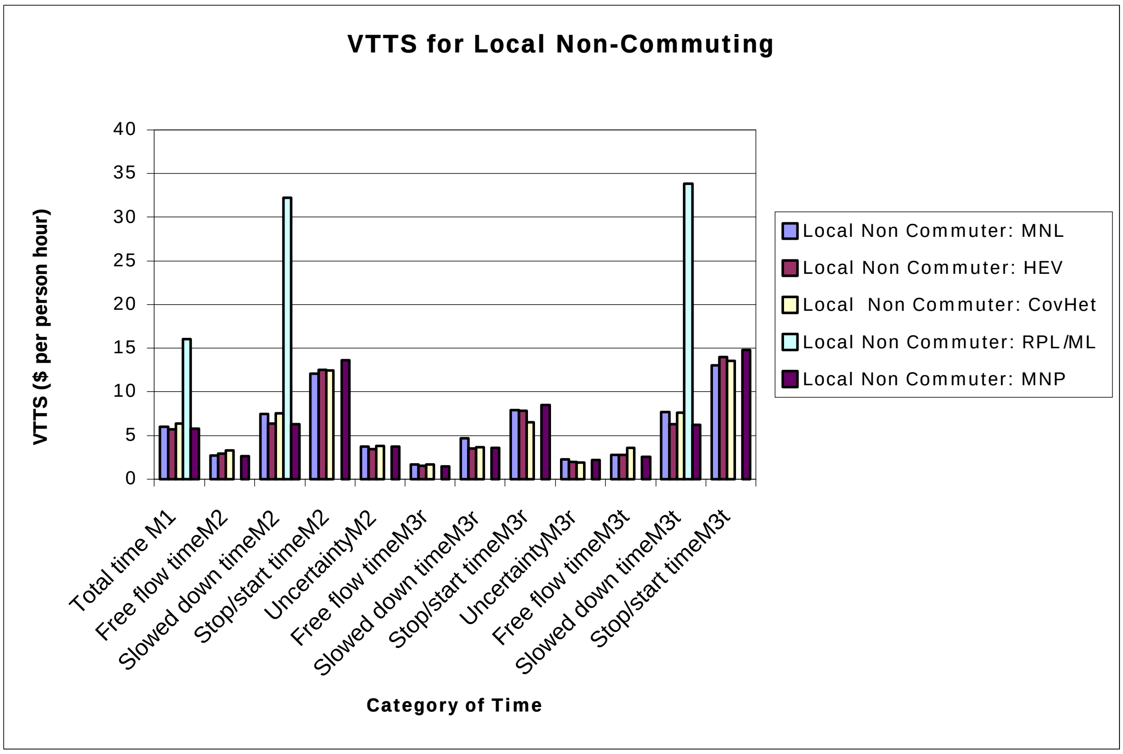
Table 6. Summary of VTTS (NZ$99 per person hour)

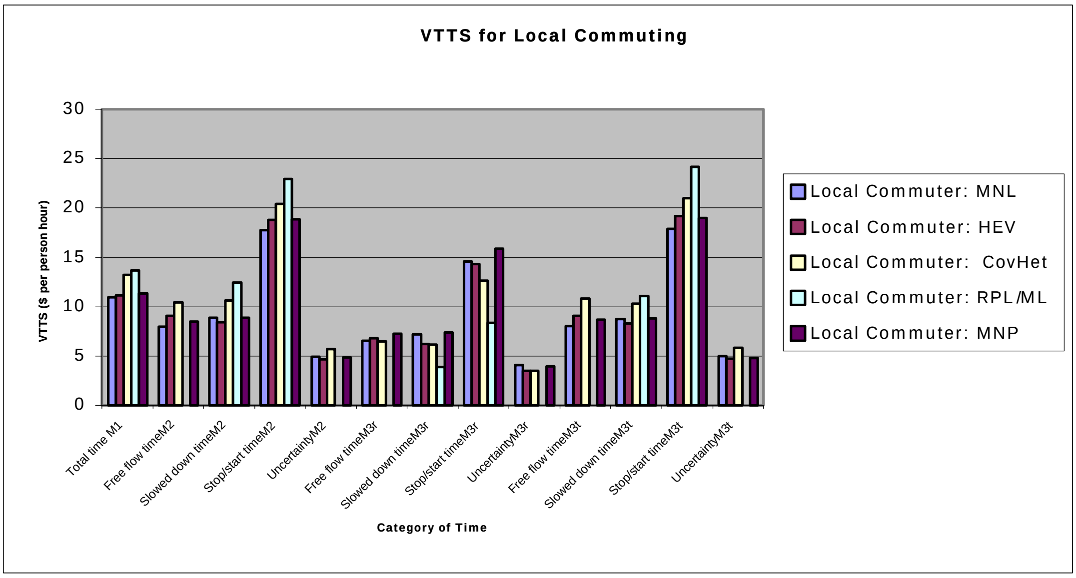
Segment	Total time*	Free flow time	Slowed down tine	Stop/start time	Uncertainty
Local commuter	***10.96-13.69***	*6.48-10.8*	*6.15-12.4*	*8.37-24.2*	*3.50-5.84*
*Local non-commuter***	***5.73-6.36***	*1.69-3.57*	*3.50-7.71*	*6.55-14.82*	*1.91-3.95*

* a simple trade-off between total time and total cost.

** excluding Mixed Logit

The evidence for urban travel supports the intercity findings in other recent studies that less restrictive choice model specifications tend to produce higher estimates of values of time savings compared to the MNL model; however the degree of under-estimation of MNL appears to be less for urban trips. As we continue to mount a case for upwardly revised estimates of VTTS, we are defacto recognising that loss of user benefits in previous road projects due to an under valuation of time savings (subject to how behavioural VTTS are translated into resource values in benefit-cost analysis).




VTTS for Local Commuting
VTTS ($ per person hour)
30
25
20
15
10
5
0
Total time M1
Free flow timeM2
Slowed down timeM2
Stop/start timeM2
UncertaintyM2
Free flow timeM3r
Slowed down timeM3r
Stop/start timeM3r
UncertaintyM3r
Free flow timeM3t
Slowed down timeM3t
Stop/start timeM3t
UncertaintyM3t
Category of Time
Local Commuter: MNL
Local Commuter: HEV
Local Commuter: CovHet
Local Commuter: RPL/ML
Local Commuter: MNP

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