**The Valuation of Non-Commuting Travel Time Savings for Urban Car Drivers**

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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 mean value of travel time savings (VTTS). Recent studies by Hensher (1997, forthcoming 2000a,b,d) and Bhat (1995) have found systematically higher VTTS for less restrictive discrete choice specifications such as the heteroskedastic extreme value 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. Given that typically over 60% of user benefits are time savings this has a major impact on both project ranking and project feasibility.

The earlier studies cited above are urban commuting and long distance intercity applications. The current paper investigates the extent to which the evidence on under-estimation transfers to urban non-commuting travel. The empirical setting is car travel in six locations in New Zealand. We contrast the values of travel time savings derived from multinomial logit (MNL) and three specifications of a mixed (or random parameter) logit (ML/RPL) model to investigate the influence of correlation between alternatives and choice sets.

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. 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 on a trip.

With a complex disaggregation of travel time and travel cost, revealed preference data (RP) may be inappropriate. There is often 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 a popular method of separating out the independent contributions of each time and cost component, providing disaggregated time values. Although we do not subscribe to stand-alone SC models for prediction, they are very defensible in valuation where the focus is on the ratio of parameter estimates[1]. The specific

[1] Predictions require knowledge of the parameter estimates, choice probabilities and attribute levels. The probabilities must be based on an RP setting and so the SC component of a data set is useful only in improving the statistical efficiency of the parameters associated with the

version of the stated choice model used herein is a switching model in which the current route attributes are contrasted with two alternative attribute packages (pivoted around the current trip attribute levels) for travel along the same route.

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 the ML/RPL model. 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 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 the multinomial logit choice model

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. 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.

Paying attention to the behavioural source of the error terms in a choice model may lead to new insights into how the model should be estimated, interpreted and applied. We have selected the mixed (or random parameter) logit model to contrast with MNL. Mixed logit is currently regarded as the most flexible and computationally practical discrete choice specification, providing a convenient approximation to multinomial probit (McFadden and Train 1997). Mixed Logit can handle unobserved heterogeneity as well as correlated choice sets.

### Mixed logit

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design attributes. Since the alternative-specific constants are excluded from the design attributes they must determined by actual market behaviour. Alternative-specific constants in an SC utility expression are uninformative for prediction.

The utility expression for mixed logit (ML) 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[2] with the variance estimated together with the mean. The selected random parameters can take a number of predefined functional forms, such as normal, lognormal or triangular. The selection of the distribution assumption for each random parameter (with alternative distributions permitted across the attribute set) is a major ongoing research area, since no one distribution has all of the desirable behavioural properties. For example, the normal allows both positive and negative values across the parameter distribution while the lognormal contains the distribution to one sign but typically produces a very thick tail that is behaviourally implausible for valuation (Hensher 2000c). The triangular distribution, used herein has a density function that looks like a tent: a peak in the centre and dropping off linearly on both sides of the centre[3]. Like the normal, it also permits negative values of travel time savings. Such unacceptable signs do not have to exist if the standard deviation of the distribution is relatively small compared to the mean such that 3 standard deviations preserves the positive valuation.

The ML form has important behavioural implications. The attributes with random parameters induce a distribution around the mean that provides a mechanism for revealing preference heterogeneity. This heterogeneity takes the form of a random effects version of unobserved heterogeneity that may be refined by making it a function of observed variables such as income and age. This is a way of revealing the specific sources of variation in unobserved heterogeneity across a sampled population. We can also account for correlation between random parameter attributes. The presence of additional terms as a representation of random tastes of each individual invariant across the choice set can induce a correlation among the utility of different alternatives (Bhat 1998, McFadden and Train 1997). It is the mixture of an extreme value type 1 (EV1) distribution for the overall utility expression and embedded 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 a mean taste weight as a component of the random component the model has been interpreted as an error-components model, where one component can take on any distributional assumption and the other component is assumed to be EV1. One can also choose to treat the random effects as

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[2] We focus on the random parameter specification that is equivalent to the error components form.

[3] Let c be the centre and s the "spread". The density starts at c-s, rises linearly to c, and then drops linearly to c+s. It is zero below c-s and above c+s. The mean and mode are c. The standard deviation is s/sqr(6). The height of the tent at c is 1/s (such that each side of the tent has area s*(1/s)*(1/2)=1/2, and both sides have area 1/2+1/2=1, as required for a density.) The slope is $1/s^2$. This specification converges much faster than the lognormal.

different across the alternatives but independent (ie different standard deviations); or as different across alternatives and inter-alternative correlated.

The correlated structure of data on choice sets that is drawn from the same individual (as in stated choice tasks) can be handled within this framework. Serially correlated error terms and serially correlated random coefficients for the alternative specific constants are exactly the same thing and in that sense, random coefficients and serial correlation are exactly the same thing. Usually, however random coefficients are given to more attributes than the alternative specific constants, and random coefficients are not typically given an AR1 specification (though they could be given that). So in practice, there is often a difference[4].

This model engenders a relatively free utility structure such that IIA is relaxed despite the presence of the IID assumption for the random components of the alternatives. That is, the ML 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 mixed logit model are given in Bhat (1997), Revelt and Train (1996), Brownstone and Train (1999), McFadden and Train (1997) and Hensher (2000b, 2000c).

From an econometric perspective, the mean of a random parameter is likely to be larger than for MNL because the mixed logit model decomposes the unobserved component of utility and normalises (through the scale parameter) the parameter estimates on the basis of part of the unobserved component. The interesting issue is the extent to which these mean estimates are relatively higher for time than for cost, which determines the direction of change in VTTS relative to MNL.

The mixed logit models are estimated by simulated maximum likelihood (SML) estimation using the Halton draws method (Bhat 1999), an alternative to the random draws approach. Numerous procedures have been proposed for taking *intelligent* draws from a distribution rather than random ones (e.g., Sloan and Wozniakowski, 1998) 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.

[4] The difference is in tradition and practice, rather than in the capabilities of the models per se. Discussions with Ken Train, Bill Greene and Chandra Bhat on this issue are greatly appreciated.

## 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[5]. 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 ($): | 0, 2, 4, 6 |

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 2000, Louviere and Hensher 2000). 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 alternative 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.

[5] There is controversy over the ability of respondents to comprehend more complex SC experiments and this will not be resolved herein; however Louviere and Hensher (2000) have looked into this issue and found no evidence to flatly reject specific design strategies. Indeed recent research by Hensher (2000b) on the long-distance sample from this New Zealand study found no systematic differences in mean VTTS due to the number of choice situations (holding the attributes and levels fixed); he did however find statistically significant differences according to the attribute range selected. As we increase the complexity of model estimation by including polynomials in the main effects (eq quadratics) and two-way interactions between design attributes, the designs with more choice situations provide the behavioural leverage necessary to separate out this fuller range of influences. Much of the commentary in the transportation literature "appears" to be limited to the simple linear main effects model.

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[6]. The assignment of levels to each SC attribute conditional on the RP levels is straightforward. An SC screen is shown in Figure 1. The data on the RP trip is identified from earlier questions (see Appendix A) and imported into the SC screen together with the attribute levels offered by alternatives A and B in accordance with the rules presented above. The data collection process is automated, accumulating respondent answers together with the design attribute levels into a data base ready for choice model estimation.

[6] 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.

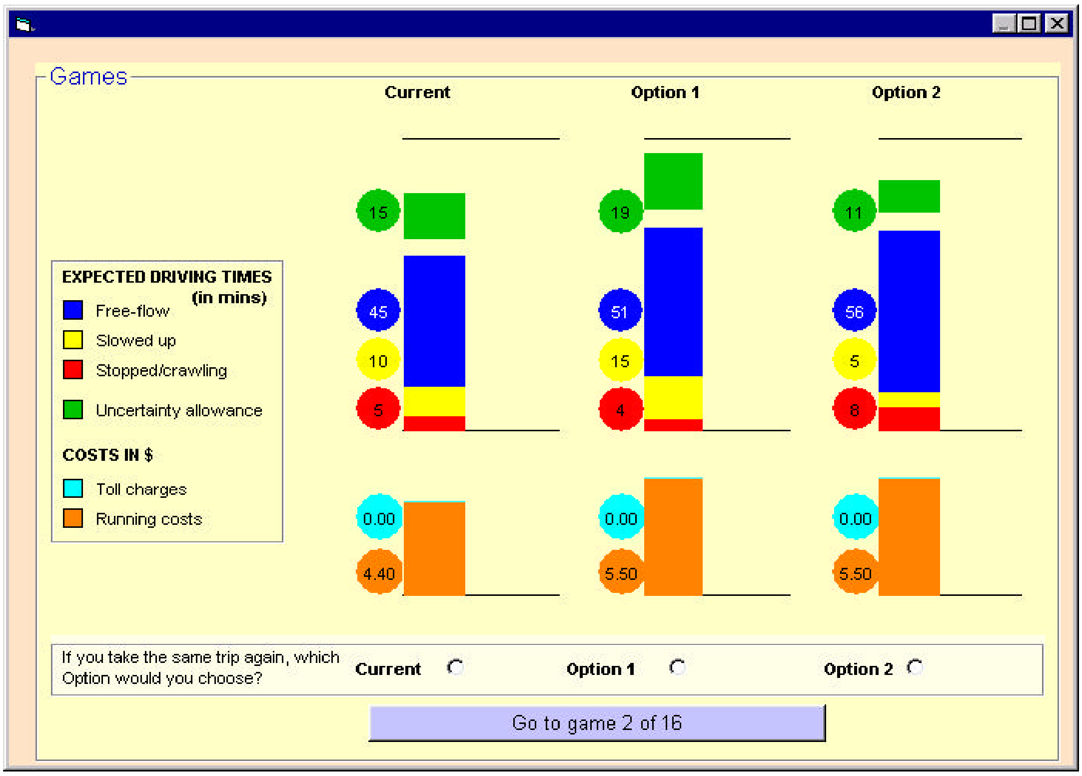


Figure 1. An example of a stated choice screen

## Empirical analysis

The survey was undertaken in late June and early July 1999, sampling residents of seven cities/regional centres in New Zealand: Auckland, Wellington, Christchurch, Palmerston North, Napier/Hastings, Nelson and Ashburton on both the North and South Islands. The main survey was executed as a laptop-based face to face interview in which each respondent was asked to complete the survey in the presence of an interviewer. Each sampled respondent evaluated 16 choice profiles, choosing amongst two SC alternatives and the current RP alternative. The main questions leading up to the SC screens are given in Appendix A. A total of 439 interviews were undertaken in the seven cities/regional centres, spread amongst four segments (local commuter, local non-commuter, long distance < 3 hours and > 3 hours). The 439 interviews represents 7,373 cases for model estimation (ie 439*16 treatments). We limit the current paper to the urban non-commuter sample of 150 respondents or 2,400 cases. The urban commuting and long-distance models are presented respectively in Hensher (2000b, d)[7].

[7] MNL models for all segments are available in Hensher, Louviere and Wallis (1999).

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 evidence on the contribution of delays to travel time. Non-commuters incur a 23.9 percentage delay time or an average delay of 4.5 minutes. The average trip length is 16.6 minutes with a trip length distribution standard deviation of 13.4 minutes.

Table 1. Summary Descriptive Statistics (mean with standard deviation in brackets)

| **Attributes** | **Mean and Standard Deviation (or percentage)** |
|---|---|
| Free flow time (mins) | 14.6 (9.9) |
| Slowed down time (mins) | 4.9 (5.6) |
| Stop/start time (mins) | 2.6 (3.0) |
| Uncertainty (mins) | 9.3 (7.3) |
| Running cost ($) | 1.7 (1.6) |
| Toll Charges ($) | 2.0 (2.3) |
| No adults | 1.9 (3.3) |
| No children | 0.6 (1.0) |
| *Time last trip (mins)* | *20.9 (10.9)* |
| *Time last trip if no congestion (mins)* | *15.9 (9.6)* |
| *Percent of trip time that is delayed time (%)* | *23.9* |
| Current trip length (kms) | 16.6 (13.4) |
| Fuel paid by driver (%) | 88.6 |
| Age of driver (years) | 46.9 (17.2) |
| Personal income ($pa) | 24128 (19490) |
| Full time work (%) | 24.9 |
| Part time work (%) | 17.1 |
| Casual work (%) | 9.2 |
| Sample Size | 2437 |

The choice models

A series of models were estimated to identify the role of each trip attribute in the SC experiment for the choice between the current car trip attributes and two other trip attribute scenarios on offer. All attributes are route abstract and 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 non-commuter models are summarised in Table 2. In the current paper we concentrate on those aspects of the models that are relevant to the derivation of the values of travel time savings. We have estimated three model forms for the fully disaggregated set of travel times and costs. Model 1 assumes that the attributes with random parameters are not correlated (hence the alternatives are independent) and the 16 choice sets are uncorrelated. Model 2 allows for correlation amongst the alternatives while preserving independence of choice sets. Model 3 permits correlation amongst alternatives and choice sets. Eight VTTS are derived (see Table 3), four for the time components based on the 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 non-linearity 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 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[8]. Although one might anticipate that a smaller perceived level of a cost attribute will tend to produce a higher parameter estimate on cost and hence lead to a lower VTTS, this has to seen in the context of the absolute levels of both running cost and tolls. In an urban setting (and consistent with the SC range of toll and running cost), we expect the toll to be higher than the running cost per trip, and hence even allowing for perceptual discounting, we hypothesise that VTTS will be higher for the cost attribute that is greatest in magnitude, which in the current application is the toll. This is confirmed by the evidence below.

All parameter estimates for the MNL model are statistically significant (t-values greater than 2.2) facilitating meaningful mean VTTS for each time component. It should be noted however that t-statistics are upwardly biased because MNL assumes independent choice sets across

[8] There are no tollroads in New Zealand and it is unclear whether electronic tolling will be the norm when introduced. This makes payment seamless although one still has to 'observe' the payment as one passes the toll capture location.

the 16 SP treatments[9]. 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). The ratio of slowed down to free flow time ranges between 2.5 and 3.75; the ratio of stop/start time to free flow time ranges from 5.3 to 9.8. The VTTS associated with stop/start time appears to be the appropriate value to use in the evaluation of congestion-reduction and incident management schemes. This suggests that in general the savings in travel time associated with noticeable traffic congestion is approximately 5 to 10 times the value for free flow travel and two to three times that for slow traffic situations.

Table 2. Final Non-Commuter Models Used to Obtain Empirical Estimates of Values of Travel Time Savings. All travel times are in minutes and costs are in dollars

| Attributes | | RPL/ML | | | |
|---|---|---|---|---|---|
| | MNL | Independent Choice Sets | | Correlated Choice Sets | |
| | | Uncorrelated Alternatives | Correlated Alternatives | Correlated Alternatives | |
| | | *Model 1* | *Model 2* | *Model 3a* | *Model 3b* |
| Free flow time | -.03048 (-2.2) | -.03368 (-2.2) | -.0399 (-2.3) | -.0300 (-2.3) | -.0245 (-.70) |
| Slowed down time | -.07750 (-4.7) | -.09639 (-4.8) | -.1024 (-4.8) | -.1345 (-3.3) | -. 1481(-2.8) |
| Stop/start time | -.1615 (-6.5) | -.17304 (-6.3) | -.1813 (-5.9) | -.2918 (-4.2) | -.2893 (-2.0) |
| Uncertainty | -.0438 (-4.2) | -.04752 (-4.3) | -.0495 (-4.0) | -.0747 (-3.8) | -.1066(-2.9) |
| Running cost | -1.180 (-9.8) | -1.2634 (-9.3) | -1.2880 (-9.7) | -1.355 (-12.3) | -1.355 (-7.3) |
| Tolls | -.6824 (-29.6) | -.7115 (-25.2) | -.7215 (-27.7) | -.7753 (-62.4) | -.8907 (-46.9) |
| *Heterogeneity in mean (only significant betas)* | | | | | |
| Free flow: Non work (1,0) | | | | | -.0552 (-.83) |
| SlowDown: Non work (1,0) | | | | | -.0564 (-.62) |
| StopStart: Non work (1,0) | | | | | -.4686 (-2.4) |
| Uncert: Non work (1,0) | | | | | .0523 (1.0) |
| *Std Dev. of beta distn* | | | | | |
| Free flow time | | 0,213 (1.41) | 0.277 (2.4) | .0054 (.09) | .2778 (-2.9) |
| Slow down time | | 0.403 (3.6) | 0.422 (1.5) | .7194 (7.1) | .4925 (3.3) |
| Stop/start time | | 0.0258 (.08) | 0.111 (0.16) | 1.491 (7.8) | 2.127 (10.3) |

[9] Practical experience suggest that despite the independence of choice set assumption that the t-statistics in this application will still be greater than the 95% confidence level. Mean estimates may also be biased which is more of a concern.

| | | | | | |
|---|---|---|---|---|---|
| Uncertainty | | 0.0163 (.13) | 0.112 (0.9) | .2460 (3.5) | .2652 (1.98) |
| *Cholesky Matrix:* | | | | | |
| FreeFlow:Slow | | | .365 (2.1) | -.59 (-4.7) | -.211 (-1.5) |
| FreeFlow:StopStart | | | .081 (.30) | -1.48 (-9.3) | -.117 (-.4) |
| SlowDown:StopStart | | | .0076 (.02) | .163 (.44) | -.969 (-3.2) |
| FreeFlow:Uncertainty | | | .109 (1.0) | -.099 (-1.4) | -.017 (-.16) |
| SlowDown:Uncertainty | | | .013 (.05) | .059 (.7) | .157 (1.4) |
| StopStart:Uncertainty | | | .014 (.02) | -.014 (-.1) | -.171 (-1.7) |
| Pseudo-$r^2$ adjusted | .4265 | .4274 | .4274 | .4659 | .5188 |
| Log-likelihood | -1510 | -1506 | -1505 | -1403 | -891.4 |

Table 3. Values of Travel Time Savings for Non-Commuters ($ per person hour, NZ$99) Average wage = $12.10/hour VTTS Standard Deviation in parenthesis.

| Attributes | | RPL/ML | | | | |
|---|---|---|---|---|---|---|
| | MNL | Independent Choice Sets | | Correlated Choice Sets | | |
| | | Uncorrelated Alternatives | Correlated Alternatives | Correlated Alternatives | | |
| *Running cost:* | | *Model 1* | *Model 2* | *Model 3a* | *Model 3b* | |
| | | | | | *No Work* | *Work* |
| Free flow time | 1.55 | 1.60 (4.1) | 1.86 (5.3) | 1.32 (ns) | 3.54 $^{ns}$ (5.0) | 1.1$^{ns}$ (5.0) |
| Slowed down time | 3.95 | 4.60 (7.8) | 4.76 (8.0) | 5.96 (13) | 9.06 (8.9) | 6.6 (8.9) |
| Stop/start time | 8.21 | 8.21 ( ns) | 8.45 (ns) | 12.93 (26.9) | 33.5 (38.4) | 12.8 (38.4) |
| Uncertainty | 2.23 | 2.25 (ns) | 2.31 (ns) | 3.31 (4.44) | 2.39 (18.1) | 4.7 (18.1) |
| *Tolls:* | | | | | | |
| Free flow time | 2.68 | 2.84 (7.4) | 3.33 (9.4) | 2.32 (ns) | 5.38 $^{ns}$(7.6) | 1.7$^{ns}$ (7.6) |
| Slowed down time | 6.82 | 8.13 (13.9) | 8.51 (14.4) | 10.4 (22.7) | 13.3 (13.5) | 9.9 (13.5) |
| Stop/start time | 14.2 | 14.6 (ns) | 15.1 (ns) | 22.6 (47.1) | 50.9 (58.3) | 19.4 (58.3) |
| Uncertainty | 3.86 | 4.01 (ns) | 4.1 (ns) | 5.78 (7.8) | 3.63 (27.5) | 7.1 (27.5) |

A potentially important finding is the increasing deviation between the mean VTTS for each time component as we relax restrictions on the relationship between the alternatives and the choice sets. For example, the MNL model has a difference of $6.66/person hour whereas Model 3a has a difference of $11.61 per person hour. The less restrictive model appears on the basis of the evidence herein to produce a greater separation of the mean VTTS across the time components. It must be recognised however that Models 2 and 3 that permit correlation across alternatives and correlation across choice sets (Model 3) provide Standard Deviation VTTS that increase noticeably as we relax the restrictions. It is noteworthy that the standard deviation VTTS is either relatively small or statistically not significant for free flow time (in contrast to the more heterogeneous components of travel time) supporting a view that the mean VTTS for free flow is a more representative estimate across the entire sample than is the mean for the other time components.

The VTTS based on the toll in contrast to running cost is systematically higher (by about 170 to 180 percent). The reasoning is linked to the higher toll in the SP alternatives, with a mean of \$3 in contrast to \$1.664 for running cost; and a higher standard deviation (\$2.24) in contrast to \$1.40 for running cost[10].

To gain further insight into the heterogeneity around the mean of the random parameters of travel time we evaluated its decomposition by all the socioeconomic and contextual characteristics in the data set. We investigated personal income (as a single variable and a number of segments), age, hours worked, trip purpose (visiting friends and relatives, shopping, social, educational), employment status (no work, casual, part time, full time) and resident city. The only covariate having a statistically significant decomposition effect was 'no work' in the context of stop/start time[11]. This attribute takes the value = 1 for individuals on a non-commuting trip who do not work (primarily home duties) and zero otherwise. The overall goodness of fit improves dramatically from .465 (model 3a) to .519. The sign of the parameter is negative suggesting a higher VTTS in non-commuting for individuals who are not employed. This is an interesting and important finding. A closer look at the data suggests that non-workers belong to households with relatively higher household incomes and more children, suggesting greater access to more financial resources and time pressures.

Model 3 is the preferred model since it allows for correlated choice sets, an issue of considerable interest to SC researchers (eg Morikawa 1994, Kim 1998). Does failure to account for serial correlation affect the VTTS? We contrast Models 2 and 3a, and undertake a two-tailed z-test on the differences in means. The null hypothesis is that there are no statistically significant differences between Model 2 and Model 3a. For a two-tailed test the results are significant at 0.05 if z lies outside the range ± 1.96. For each of the time components (free flow, slowed down stop/start, uncertainty), the respective z values are 6.71, -6.67, -13.85 and -18.11. Hence we can reject the null hypothesis of no significant differences for all time components. Indeed the null is rejected for the 0.01 level. Thus failure to account for choice set correlation has a statistically significant (downward biased) effect on the mean VTTS.

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[10] Juan de Dios Ortuzar has suggested (in a personal communication, June 2000) that the cost of a given trip is much more clearly associated with a toll than to running cost such as fuel which applies to more trips. For this reason there is a preference to calculate VTTS only on the basis of tolls or other direct out of pocket cost, and that good practice should encourage this emphasis.

[11] A sample size of 150 individuals may limit the role of covariates.

## Conclusion

This study has focused on the influence of alternative assumptions on the random components of the underlying utility expressions representing the preferences of non-commuter car drivers for alternative bundles of trip attributes. 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 to recognise the broadening range of monetary costs that impact directly on a trip.

We have also taken into account the influence of correlation across alternatives and across choice sets. The evidence herein for urban non-commuter travel supports the intercity and urban commuter findings in other recent studies that less restrictive choice model specifications tend to produce higher mean estimates of values of time savings compared to the MNL model. The degree of under-estimation of MNL appears herein to be due mainly to travel time beyond free flow; however statistical tests for the impact of ignoring serial correlation find strong evidence of underestimation even for the mixed logit model with uncorrelated choice sets. We also find that the greater the heterogeneity of travel time, the greater the deviation between the MNL and mixed logit results (for the fully specified model 3a).

If the case for upwardly revised estimates of mean VTTS continues to be supported in further studies, we are defacto recognising the 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).

## Acknowledgments

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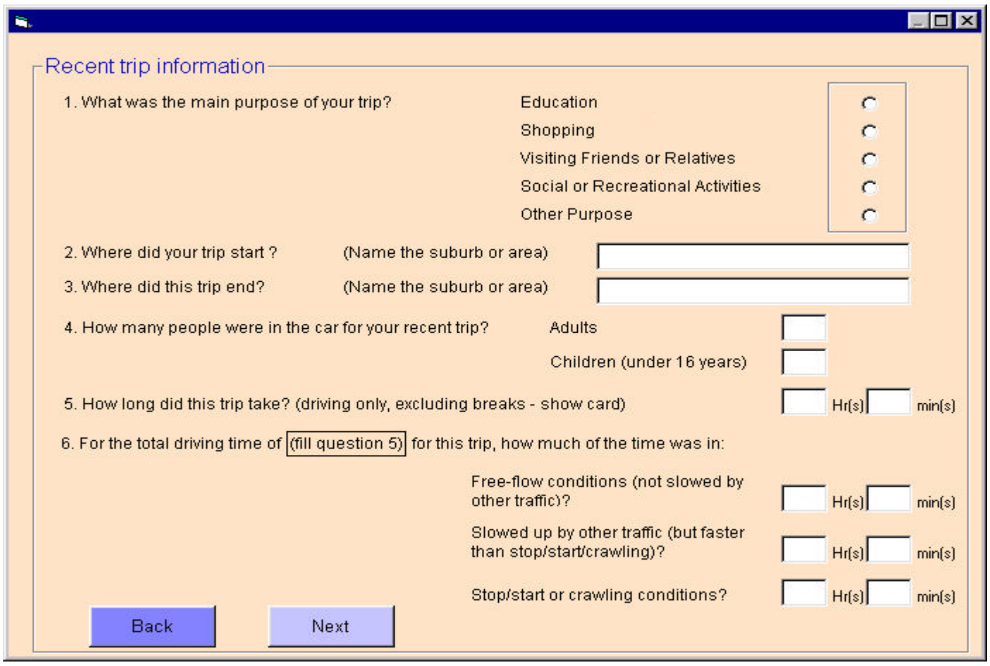
## Appendix



Recent trip information

1. What was the main purpose of your trip?
   - Education
   - Shopping
   - Visiting Friends or Relatives
   - Social or Recreational Activities
   - Other Purpose

2. Where did your trip start ? (Name the suburb or area)

3. Where did this trip end? (Name the suburb or area)

4. How many people were in the car for your recent trip? Adults / Children (under 16 years)

5. How long did this trip take? (driving only, excluding breaks - show card) Hr(s) min(s)

6. For the total driving time of (fill question 5) for this trip, how much of the time was in:
   - Free-flow conditions (not slowed by other traffic)? Hr(s) min(s)
   - Slowed up by other traffic (but faster than stop/start/crawling)? Hr(s) min(s)
   - Stop/start or crawling conditions? Hr(s) min(s)

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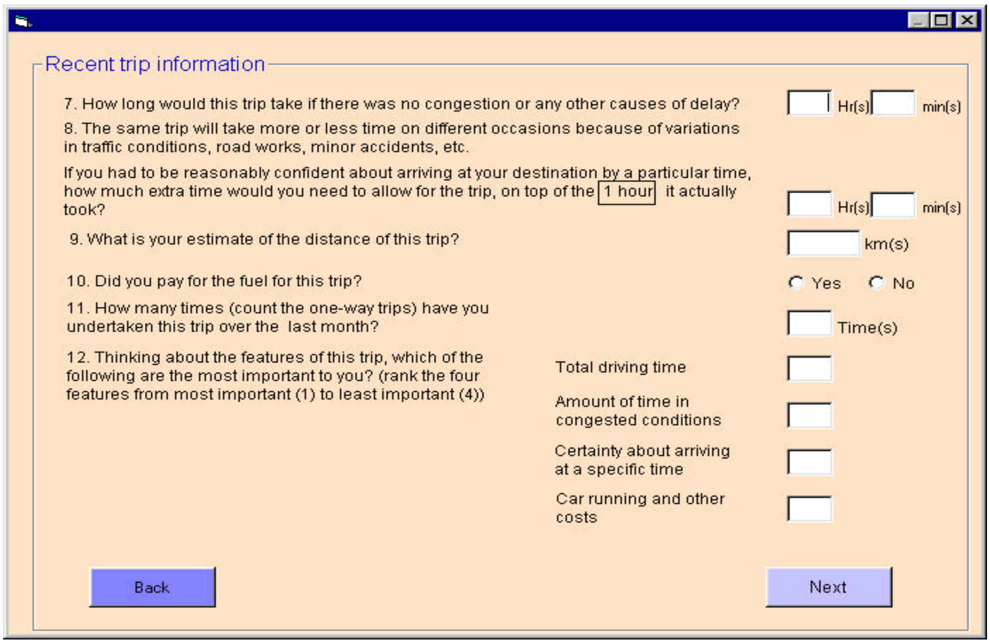

Recent trip information

7. How long would this trip take if there was no congestion or any other causes of delay? Hr(s) min(s)

8. The same trip will take more or less time on different occasions because of variations in traffic conditions, road works, minor accidents, etc.
If you had to be reasonably confident about arriving at your destination by a particular time, how much extra time would you need to allow for the trip, on top of the 1 hour it actually took? Hr(s) min(s)

9. What is your estimate of the distance of this trip? km(s)

10. Did you pay for the fuel for this trip? Yes No

11. How many times (count the one-way trips) have you undertaken this trip over the last month? Time(s)

12. Thinking about the features of this trip, which of the following are the most important to you? (rank the four features from most important (1) to least important (4))
   - Total driving time
   - Amount of time in congested conditions
   - Certainty about arriving at a specific time
   - Car running and other costs

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