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Measurement of Valuation of Travel Time Savings

By

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ABSTRACT: The value of travel time savings (VTTS) is a critical parameter in transport project appraisal and through its application produces the dominating user benefit, typically 60% of traditionally quantified user benefits. Beesley's work in the 1960's laid the foundation for much of the subsequent applied research, especially in respect of measurement and interpretation. This paper revisits Beesley's contribution in the context of the 1960's and shows the subsequent development of his ideas.

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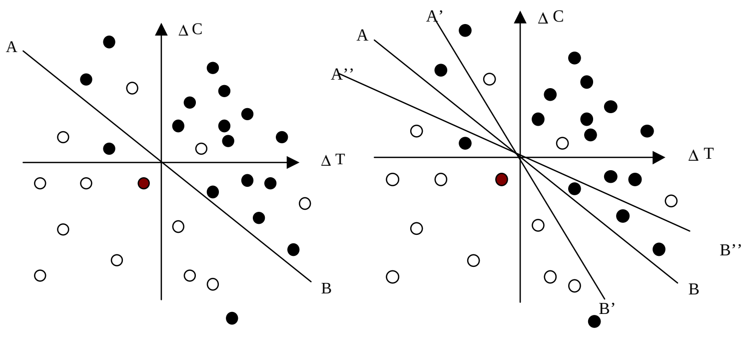
Introduction

One of the themes in transport economics and travel demand research that emerged in the 1960's was how to value time spent in travelling. Postwar transport projects such as the Victoria Line underground extension in London (Foster and Beesley 1963) and the M1 motorway between Birmingham and London (Coburn, Beesley and Reynolds 1960) had identified the dominating role of travel time savings in the determination of user benefits and in the justification, in benefit-cost terms, of such infrastructure investment. This was the beginning of a formal framework for the economic appraisal of transport projects. Munby in commenting on the Victoria Line study (reported in Foster and Beesley (1963)) states that "Time savings are, as in the M1 study, one of the most important items of benefit, 25% of the total are time savings of vehicle-users, 8% are time savings of the Victoria Line traffic which diverts from buses." Munby then goes on to say that "…Some figure has to be put in for these savings, but they are bound to be largely arbitrary…. Until we know more about the actual benefits which travellers of all sorts gain from saving time. This requires research into the actual purposes of journeys, and into the possibilities, in practice, of making use of vehicles and time saved".

Beesley responded to the challenge to identify an appropriate method of valuing travel time savings, publishing his classic piece in Economica in 1965. For the next seven years the literature studied the Beesley contribution in great detail (eg Quarmby 1967, Harrison and Quarmby 1969, Rogers et al 1970, Davies and Rogers 1973, Mansfield 1970, Department of Environment 1976,); recently revisited by Gunn (2000). What Beesley did was to suggest a framework for the measurement of the value of travel time savings that focussed on conditions for successful measurement. Now known as the Beesley Graph, Beesley studied the binary choice between public transport modes through an evaluation of two attributes – travel time and travel cost. He divided the combinations of differences in cost and time into four possibilities in which alternative 1 (compared to alternative 2) was more expensive and quicker, more expensive and slower, less expensive and quicker, less expensive and slower. Through a graphical representation of the survey data (Figure 1), he identified traders and non-traders; suggesting that the latter provide no useful information for valuation.



AB given by $\Delta C = \theta \Delta T$

Figure 1 The Beesley Graph

The left hand diagram sets out the standard Beesley graph with each sampled individuals time and cost circumstance represented by a dot. The challenge for Beesley was to find a way of drawing a line through the data that would minimise the misclassification of prediction. Given knowledge of an individual's chosen mode Beesley established a line such as AB to produce a certain number of cases where the wrong choice of an alternative would be predicted in the 'if nothing other than time and money mattered' case, and another produced less such cases, the second line would be preferred, and would then be tested against other possible lines until 'the best' was found (Gunn 2000). The right hand diagram in Figure 1 illustrates this search mechanism.

The line AB in the left-hand diagram represents the points at which time savings are exactly offset by cost losses, or time losses exactly offset by cost gains. Above this line, we would expect alternative 2 to be chosen all the time (if only time and money mattered) and below alternative 1 all the time. Each ' ' symbol denotes one person's choice (in the sense of specifying the time and cost differences between the alternatives) and the outcome (in this case, as a choice of alternative 1). Similarly, the ' ' symbol denotes a choice of alternative 2. As would be expected, we have created a plot with mostly choices of alternative 2 in the upper right hand quadrant, and of alternative 1 in the lower left. In the right-hand side diagram, AB is the 'best' discriminator of the three gradients evaluted although another gradient may be better than all three. This gradient identifies the average VTTS.

The Beesley approach is simple and intuitively appealing. Its simplicity however has limited its generalisation. Quarmby (1967) was the first review and critique of the Beesley approach as a misclassification minimisation method, adopting a multivariate discriminant analysis approach to establish the weights for time and cost that give rise to minimum misclassification. Quarmby criticised the Beesley method because of its extreme sensitivity to the position of points near the threshold – what is the relationship between the gradient and number of misclassifications (ie deep U shaped or mere undulation?). Other authors such as Rogers et al (1970) have recognised the problems with a diagrammatic approach when the number of attributes being traded increases beyond two and when unobserved attributes (represented at their mean by the alternative-specific constant) play a role in defining the relative utility of competing alternatives. Under these generalisations the line of misclassification does not pass through the origin. This is an unnecessary restriction on the relative disutilities of alternatives and is equivalent to assuming that the marginal value of time savings equals the average value (Hensher and Goodwin 1978, Hensher 1978).

The argument that non-traders do not add direct evidence about gains and sacrifices in time was debated in a number of papers (eg Department of Environment 1976) and rejected. In a correctly specified choice model, the dominants as well as the traders contribute the same level of information to the estimation process, and importantly when the full set of attributes, observed and unobserved, are taken into account, the so-called *illogical* choices may look consistent with the axioms of revealed preference.

Indeed the inclusion of the alternative-specific constant makes impossible the exclusion of non-traders which is a strictly binary attribute construct.

Beesley also recognised many of the limitations of his earlier work and in his papers published between 1970 and 1979 set out the conditions for successful measurement of VTTS. The following quote from Beesley (1973, 1974) illustrates the insights he brought to the topic as well as highlighting a number of major issues that continue to focus current research:

> *"Our starting point is that of a study consisting of actual binary choices by consumers. We assume that the best evidence derives from observations of actual choices. We ground this on assertions, not to be further considered, that evidence of what consumers do, or have done, as part of their experience is better than what they might do or seem to do in hypothetical conditions set up by the observer (laboratory tests). Also we assert that, as a matter of practice, consumers can give far better evidence when choice is confined to two options than when choice is multiple; i.e. consumers tend to think in terms of, and more accurately report, single alternatives. Having said this, we immediately encounter the difficulty that a special weight is then thrown on the assumptions about, and evidence for, the homogeneity of classes of people to whom the measurements are held to apply. ... One needs to classify consumers both because one has to identify, operationally and as economically as possible –i.e. with the minimum of elaboration – who is to be affected by a policy change, new projects or investment, etc, and because one hopes thereby to ease the problem of estimating within acceptable error limits – one chooses to group consumers together to obviate or lower the cost of explanation. … For example, if we can regard consumers within defined income brackets as homogeneous, it is a great computational convenience. But this may, on the one hand, not serve to illumine behaviour; and on the other may not distinguish among policy options in a useful way."*

This quote shows how insightful Beesley was about a number of econometric aspects of procedures for deriving time-cost trade-offs. He raised many of the important contemporary issues in valuation within a discrete choice setting, such as choice set size; sources of preference data, especially stated preference (SP) versus revealed preference (RP) data (with the recent recognition of the benefit of enriching RP data with SP data[1] in a Bayesian sense); the heterogeneity of travel time; and how to handle unobserved heterogeneity through random parameter and mixed logit models to produce distributions of VTTS. The last 35 years have in many ways been a formalisation of what Beesley noted in the 1960's[2]. He understood the need for good econometrics even though it was not his forte[3] '…. Future studies, should concentrate on the steps likely to

[1] He was unaware at the time of the rich opportunities that were to unfold in formalised stated preference methods that mirrored the structure of revealed preference data (in contrast to the hypothetical-based attitudinal approaches on the 1960's and early 1970's). Subsequently he has said in verbal discussions that the SP approach has much merit.
[2] Between 1967 and 1997 the Journal published 21 papers on VTTS (Starkie 1998), one indicator of its importance.
[3] Although one reviewer in 1973 described his *Economica* paper as a strong econometric piece! (Department of Environment 1976)

lead to better estimation procedures' (Beesley 1973, 185). The following sections show progress in the spirit of Beesley's insights.

Incorporating the Beesley Insights into Measurement of VTTS

Three facets of valuation have emerged as potentially major influences on VTTS: 1) the heterogeneity and non-linearity of travel time 2) the design strategy for stated preference experiments, the most popular data tool for valuation and 3) the exploration of alternative error covariance structures of discrete choice models. To illustrate progress and highlight the ongoing challenges, we focus on the valuation of travel time savings for car travel in the (New Zealand) long distance non-business market (up to three hours) utilising stated preference methods, less restrictive error covariance models and a rich specification of the heterogeneity of travel time. In particular, we move beyond a focus on the heterogeneity of travel time that distinguishes in-vehicle and out of vehicle time to a focus on the composition of in-vehicle 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 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 (see also Senna 1994).

With a richer disaggregation of travel time, revealed preference data (RP) is usually inappropriate (at least as the only source of attribute-trading). There is typically too much confoundment in RP data, best described as 'dirty' from the point of view of statistical estimation of the individual influences on choice. Some attribute levels may not be observed in the RP data and the predictor variables (attributes, covariates) may exhibit high or extreme levels of multicollinearity consequent on market forces, technology and sampling considerations.

An alternative is a stated preference (SP) 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. This literature is extensive (see Hensher 1994, Louviere et al 2000). 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 (Gunn 2000). However, SP experiments have many features that can influence the resulting VTTS. In particular it is thought that the estimates are sensitive to the design of the SP experiment, especially 1) the number of alternatives in a choice set, 2) the number of choice sets (or treatments) evaluated and 3) the range and levels of the time and cost attributes being traded.

Theoretical considerations suggest that VTTS is likely to be under-estimated in multinomial logit (MNL) models because an element of the unobserved influences on travel choices is 'forced' into the parameter estimates of the observed effects when the strict independently and identically distributed (IID) condition is imposed on the utility functions. Theory also suggests that this impacts on the time attributes more than the cost attributes because many of the unobserved attributes are more correlated with travel time than travel cost (Jara-Diaz 1996). Thus the suppressed scale parameter defining the inverse of the standard deviation of the random component of a utility expression associated with an alternative in a discrete choice set adds relatively extra parameter power to the travel time estimate, reducing the VTTS.

We want to investigate how the structure of the unobserved effects conditions the form of a discrete choice model, and hence the possible mis-inference from the simpler MNL specification. In particular, we want to identify the implication for VTTS of covariance amongst alternatives, the presence of individual specific (random) effects or heterogeneity, and differential variance of the unobserved effects. We expect to find that a more comprehensive definition of time heterogeneity, a carefully structured SP design to accommodate more complexity in attributes, and less restrictive error covariance structures will result in VTTS that are different from estimates used in economic evaluation of transport projects, currently derived from simple SP designs and MNL models with limited time heterogeneity. Since time savings are the greatest single user benefit the findings will be critical in either reinforcing or questioning current practice.

However, what is of particular interest is the interface between the SP design strategy and the error covariance structure (Bates 1988), since it is increasingly argued (see Louviere, Hensher and Swait 2000 for details) that the role of the properties of the error covariance matrix (especially the scale parameter) is very sensitive to the quality of the data. Louviere and Hensher (2000) suggest that "Accumulating evidence from various literatures, especially in marketing, psychology and transportation, provides support for the desirability of combining sources of preference data as a way of transferring increasing power of understanding of travel behaviour from the econometrics of a model to the underlying data inputs".

In much of the theoretical and empirical work undertaken in the random utility theory (RUT) paradigm the ε's are a unidimensional component associated with each choice option. This view of the ε's has obfuscated the fact that these random components of utility are multidimensional. That is, the ε's are better thought of as variance components that include variation within-subjects, between-subjects and variation due to the measurement instrument. In any given empirical study, unless the study is designed to separate these components, the data and model outcomes is likely to be confounded with the variability and cannot be separately identified. Of these components, there has been recognition of between-subjects variation especially in the form of preference parameter heterogeneity, but there has been little recognition that there also can be between-subjects variation in model forms (Kamakura et al 1996) as well as preference parameters (Louviere and Hensher 2000)

The statistical efficiency of choice experiments is as much a behavioural as a statistical issue (as Beesley noted). In particular, unlike the objects of analysis in many classical statistical experiments and indeed in the mathematical and statistical theory that underlies design optimisation, humans *interact* with choice experiments in ways not previously considered by transport analysts. In the following sections, we set out the more general error covariance model and the specific stated preference experiment to be used in developing VTTS to contrast with the MNL model.

Random Parameter (Mixed) Logit

The comments made by Beesley in 1965 about the importance of accounting for differences in the heterogeneity of travellers recognised the importance that unobserved heterogeneity plays in the valuation of travel time savings. Although Beesley chose personal income as the indicator of heterogeneity and sampled only individuals in a common band of personal income for his descriptive (ie graphical) analysis of a binary trade-off between time and cost, he recognised that there may be many socioeconomic criteria that distinguish preferences that need to condition the analysis. We now recognise that not all such criteria can be represented by a set of individual-specific socioeconomic influences and that a random effects term might be introduced to capture the ‘residual’ unobserved heterogeneity. In addition this can be captured through a random parameter specification of the discrete choice model in which we allow subsets of attributes to have a mean and a standard deviation of the parameter estimate, in addition to correlation amongst these random parameters across the alternatives in the choice set. We now have the econometric capability of pooling data across all socioeconomic segments and accommodating unobserved heterogeneity in a single model.

The utility expression for random parameter logit (RPL) model is of the same form as 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 1997, Revelt and Train 1999). It is the mixture of an extreme value type 1 (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 to give $\nu_{qk}x + \varepsilon_i$, 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.

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. This is a way of revealing the specific sources of variation in unobserved heterogeneity across a sampled population.

The random parameter/mixed logit model does not have a closed form solution (unlike the MNL model) and so it is approximated numerically through simulation by the method of simulated maximum likelihood (SML). Numerous procedures have been proposed for taking *intelligent* draws from a distribution (Sloan and Wozniakowski, 1998; Morokoff and Caflisch, 1995). Random draws are commonly adopted using psuedo-random sequences for the discrete points in a distribution. Recently Bhat (1999) showed that the coverage of the random utility space is more representative by a quasi-Monte Carlo approach that uses non-random and more uniformly distributed sequences within the domain of integration (Bhat 1999, 3). This procedure, known as Halton sequences, offers the potential to reduce the number of draws that are needed for estimation of RPL/ML models, thereby reducing run times, and/or reducing the simulation error that is associated with a given number of draws. Bhat (1999) 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. 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 ten times faster). Hensher (1999) 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 investigated he concluded 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 very similar). This is a phenomenal development in the estimation of complex choice models. Fifty draws are used in the current study.

Design of the Stated Preference Experiment

The focus of the empirical inquiry is on the valuation of non-business travel time savings for car drivers undertaking long distance trips (up to three hours) between major urban areas in New Zealand. The data was collected in 1999 and is detailed below. The central element of the survey instrument was 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 SP 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, $5, $10, $15

Including the current (ie revealed preference (RP)) alternative, described by the exact same six attributes as the two SP 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. The levels of the attributes for both SP 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, divided into four blocks of 16 randomly assigned choice sets. We allocated the four blocks of 16 to each set of four sequential respondents 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 for the next four respondents. 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 SP 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).

An SP screen is shown in Figure 2. The data on the RP trip is identified from earlier questions and imported into the SP 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.

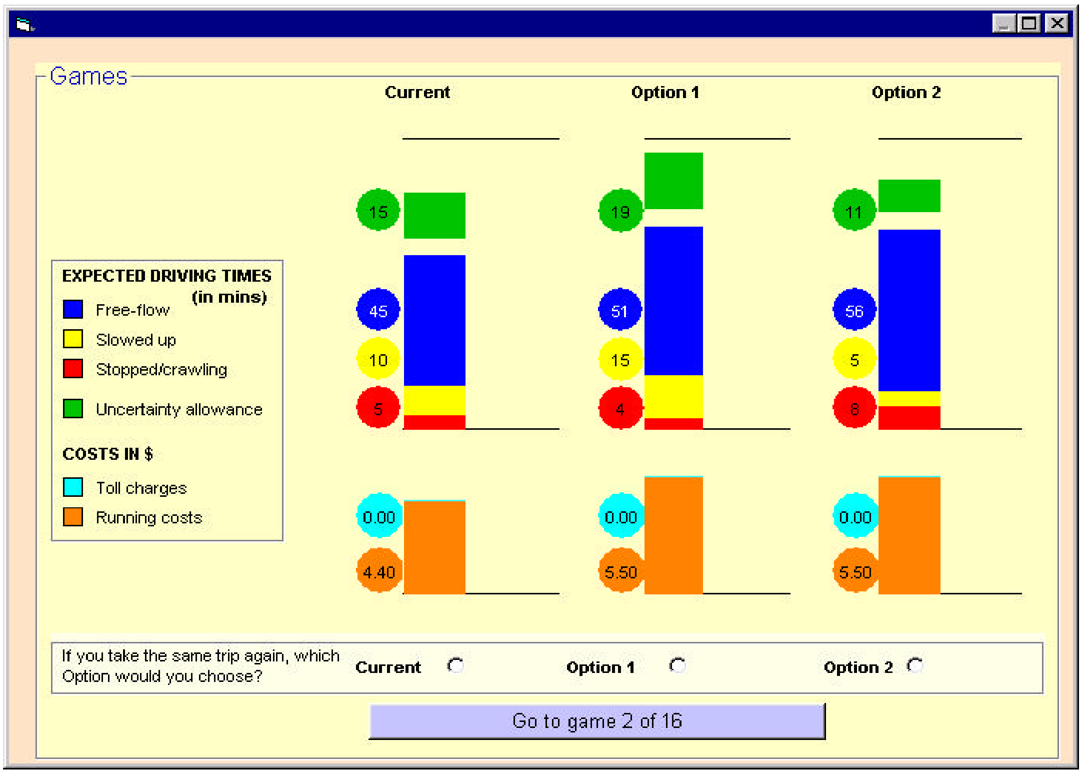


Figure 2. An example of a stated preference screen

The Empirical Study

The main survey was undertaken in late June and early July 1999 as a laptop-based face to face interview in seven cities/regional centres in New Zealand [4], spread amongst four trip segments (local commuter, local non-commuter, long distance < 3 hours and long distance > 3 hours). We focus on the long distance trips up to three hours (see Hensher 1999 for a discussion of local travel), a sample of 198 individuals and 3168 trip circumstances.

Descriptive statistics are summarised 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 trips time that is free flow in contrast to the current time which includes all sources of delay. 15.2% of long distance trip time up to 3 hours is the result of delays at present. For an average trip length of 112.7 minutes offered in the experiment for the current and alternative SP trips, there is an additional average 23.5 minutes of time evaluated as the extra time allowed for to ensure arrival at the destination by a particular time.

[4] Auckland, Wellington, Christchurch, Palmerston North, Napier/Hastings, Nelson and Ashburton.

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

Free flow time (mins)	86.5 (40.6)	Time last trip (mins)	106.9 (38.1)	Fuel paid by driver (%)	88.3
Slowed down time (mins)	15.5 (13.5)	Time last trip if no congestion (mins)	90.7 (38.7)	Age of driver (years)	47.2 (15.9)
Stop/start time (mins)	10.7 (11.0)	Percent of trip time that is delayed time (%)	15.2	Personal income ($pa)	28662 (19838)
Uncertainty (mins)	23.5 (22.9)	Current trip length (kms)	131 (60.8)	Full time work (%)	46.4
Running cost ($)	13.3 (6.6)	No adults	2.0 (1.4)	Part time work (%)	16.5
Toll Charges ($)	4.4(5.2)	No children	0.5 (0,87)	Casual work (%)	7.5

The final MNL and RPL models are summarised in Table 2 including the lower triangular Cholesky factor of the preference variance-covariance matrix for the (statistically significant) correlated random parameters. Three models of varying degrees of disaggregation of time and cost have been estimated for each of MNL and RPL. We have allowed for random parameter estimates for travel time as well as correlation amongst these random parameters (ie across the three alternatives). All mean parameter estimates are statistically significant, as are the parameters for the standard deviation except for trip time uncertainty.

There is clear evidence of preference heterogeneity (or traveller-specific taste parameters), supporting Beesley's concern without having to approximate homogeneity of classes of travellers by specific socioeconomic variables. As long as we accept that this taste parameter variability is (in our case) lognormally distributed we can use the mean and standard deviation of each random parameter to produce a distribution of attribute marginal (dis)utilities across the sampled population segment.

The cost attributes have fixed parameters. Ruud (1996) has pointed out that mixed logit models have a tendency to be unstable when all parameters are allowed to vary. Fixing the cost parameter resolves this instability. If the cost parameter is allowed to vary, the distribution of VTTS is the ratio of two distributions, a Cauchy distribution, which is inconvenient to evaluate. With a fixed cost parameter, VTTS is distributed the same as the parameter of travel time. Furthermore the choice of distribution to use for a cost parameter is problematic (Revelt and Train 1996). This parameter is necessarily negative, such that a normal distribution is inappropriate. With a lognormal distribution (which assures that the price parameter is always negative), values very close to zero are possible, giving very high (implausibly high) values of travel time savings.

The simple two-attribute model is the multivariate equivalent of Beesley's graphical model. The mean VTTS based on time homogeneity (Model 1) is higher (by 8%) for the RPL than MNL specification. This directionality carries over to time decomposition for free flow time, with percentage increases between 25.9% and 35.2% for Models 2 and 3. The mean estimates of VTTS are in contrast much more similar (up to a maximum of 8% difference) between the MNL and RPL models for stop/start time and slowed down time. This suggest that after accounting for any differences due to preference heterogeneity that the MNL model's underestimation of the mean overall VTTS is attributable to the differences in the free flow value. Indeed if we assume that we assign the appropriate VTTS to the circumstance on offer after someone has switched to an improved route (eg a toll road with a higher amount of free flow travel time), as is the correct procedure for determining a user time benefit (in contrast to the route they switched from) then the MNL model would seriously underestimate the time benefits between 8% and 30%. The higher mean VTTS for mixed logit than MNL confirms accumulating evidence that the more restrictive MNL specification undervalues the mean VTTS (Hensher 1999 and forthcoming).

An interesting and controversial aspect of Model 2 is the establishment of separate parameter estimates for the two cost components – fuel and toll. Beesley (1974) recognised the challenge in defining car costs (a reason for him specialising his empirical work to public transport options). This concern continues for revealed preference data where an individual is either asked to indicate the cost of car travel (a reported perceived cost) or the analyst imposes a constant cost per kilometre and converts it to trip cost given knowledge of the distance travelled. Beesley (1973, 178-179) states that "…each of the [RP] studies involving car chose an average car 'cost' necessarily rather arbitrary" and then suggests "…one might be inclined to opt for the higher values [of time savings] as more representative of 'opportunity cost' of time, because they avoided the difficulties". The use of SP methods largely overcomes these valid concerns by offering pre-designed levels of cost with sufficient variation to produce more robust estimates of the role of cost per se. However Beesley did not comment on the possibility of having a number of cost attributes, distinguished in terms of the manner in which the components of cost are outlayed. The popularity of evaluating toll roads and alternative toll collection methods (ie electronic, automatic and cash at a booth) has produced a debate on the extent to which one associates a unit of fuel cost and a toll as sharing a common parameter estimate. It is reasonable to assume that as the outlay mechanism converges to a common base (as is the situation for electronic tolling using offsite collection such as EFTPOS), the differences in marginal utility will narrow if not disappear.

In model 2, the relativity of the VTTS for fuel and toll-based cost is linked to the levels of cost on each component. As reported in Hensher (1999), the urban models produced higher mean VTTS for toll-based cost than fuel-based cost, the opposite to the evidence here where there is a systematically lower VTTS associated with the toll-based calculation. The reason is linked to the relative magnitudes of fuel and toll cost offered in the SP exercise. For long distance travel up to 3 hours, the average fuel cost is $13.80 (sd=6.6) compared to the average toll cost of $6.57 (sd=5.2). In contrast, for urban travel, the average fuel cost was $2 compared to $3 for toll cost. There is a very important message here, supporting the contention that the range and levels of attributes in an SP design has a noticeable influence on the resulting VTTS (see new evidence in the next section). For long trips the fuel cost starts to build up and the perception of the difference in cost starts to favour the toll. This clarifies a generally held (and incorrect) view that individuals are necessarily more sensitive to toll than to fuel cost and hence would be expected to have higher VTTS in a time-toll cost trade than a time-fuel cost trade. This only holds if the toll is greater than the fuel cost *as perceived* by the traveller. In a very real sense the SP method eliminates the lumpiness argument unless it is shown that reference to the mechanism for extracting a toll has a statistically significant influence on the marginal utility of a toll compared to the fuel cost. In the absence of such a 'collection' attribute, it is reasonable to assume that the differences in marginal utility are due to the magnitude of the outlay.

Table 2. Random Parameter (Mixed) Logit Models for Long Distance Travel in New Zealand up to 3 hours. All travel times are in minutes and costs are in dollars

Attributes	MNL Base	RPL Model
Model 1:		
Total time	-.0382(-11.1)	-.0433 _-7.8)
Total cost	-.2638 (-19.5)	-.2771 (-15.4)
Std Dev of Parameter Distribution		
Total time		.02747 (2.2)
Total cost		
Cholesky Matrix:		
Tottimr		.02747 (2.2)
Pseudo-r^2	.405	.407
Log-likelihood	-689.5	-689.4
Mean value travel time savings		
Total time	8.69	9.38
Model 2:		
Free flow time	-.0151 (-3.4)	-.0246 (-3.4)
Slowed down time	-.0557 (-6.8)	-.0680 (-5.4)
Stop/start time	-.1104 (-11.3)	-.1431 (-7.9)
Uncertainty	-.0207 (-3.4)	-.0238 (-2.7)
Fuel cost	-.1647 (-5.7)	-.2143 (-5.4)
Toll Cost	-.2649 (-17.5)	-.3212 (-11.9)
Std Dev of Parameter Distribution		
Free flow time		.04118 (2.7)
Slowed down time		.09459 (3.1)
Stop/start time		.08449 (2.1)
Uncertainty		.01387 (0.2)
Pseudo-r^2	.471	.476
Log-likelihood	-611.2	-603.6
Cholesky Matrix: Significant effects only		
Slow:stop/start		.07572 (1.92)
Mean value of travel time savings: fuel cost		
Free flow time	5.48	6.90
Slowed down time	20.29	19.06
Stop/start time	40.21	40.12
Uncertainty	7.51	6.68
Mean value of travel time savings: toll cost		
Free flow time	3.41	4.61
Slowed down time	12.62	12.7
Stop/start time	24.99	26.7
Uncertainty	4.67	4.46
Model 3:		
Free flow time	-.01507 (-3.4)	.0422 (-3.4)
Slowed down time	-.05429 (-6.7)	-.0653 (-5.3)
Stop/start time	-.1168 (-12.1)	-.1524 (-8.1)
Uncertainty	-.0209 (-3.5)	-.02456 (-2.8)
Fuel plus toll cost	-.2520 (-17.7)	-.3129
Std Dev of Parameter Distribution		
Free flow time		.0419 (2.8)
Slowed down time		.0962 (3.3)
Stop/start time		.0964 (2.6)
Uncertainty		.01352 (.18)
Pseudo-r^2	.467	.473
Log-likelihood	-616.9	-608.1
Cholesky Matrix: Significant effects only		
Slow:stop/start		.0918 (2.5)
Mean value of travel time savings		
Free flow time	3.58	4.66
Slowed down time	12.93	12.56
Stop/start time	27.8	29.2
Uncertainty	4.99	4.72

The RPL model provides estimated parameters of the standard deviation of each travel time component to calculate car traveller's conditional taste densities. To establish a distribution of VTTS to accommodate preference heterogeneity, we have to calculate $E(b)$ for each individual using the point estimates of the population parameters of the distribution, μ, given in Table 2. Although each sampled traveller knows his own value of μ, the analyst has limited information, supported by the maintained distributional assumption, in our case lognormal. With a lognormally distributed parameter estimate profile for a travel time attribute, given the standard deviation, we have to draw a sample of estimates that comply with the assumed distribution and then use these together with the fixed cost parameter estimate to produce a distribution of VTTS. This can be achieved by simulated draws. Using the lognormal distribution we start with 10,000 randomly generated 'observations' and sample draws of 1000 randomly with replacement repeated 1000 times. The findings are summarised in Figure 3 for twenty draws that represent the range of results for 1000 draws. We limit this illustrative application to Model 1.

The most interesting result is the systematically higher mean VTTS in the range $11.568 to $12.098 (with a range for the standard deviation from $5.62 to $6.38) compared to the unadjusted mean of $9.38 in Table 2. The reasoning for this is unclear but it adds further empirical support to a view that VTTS in practice as derived from more restrictive choice models tend to be underestimated.

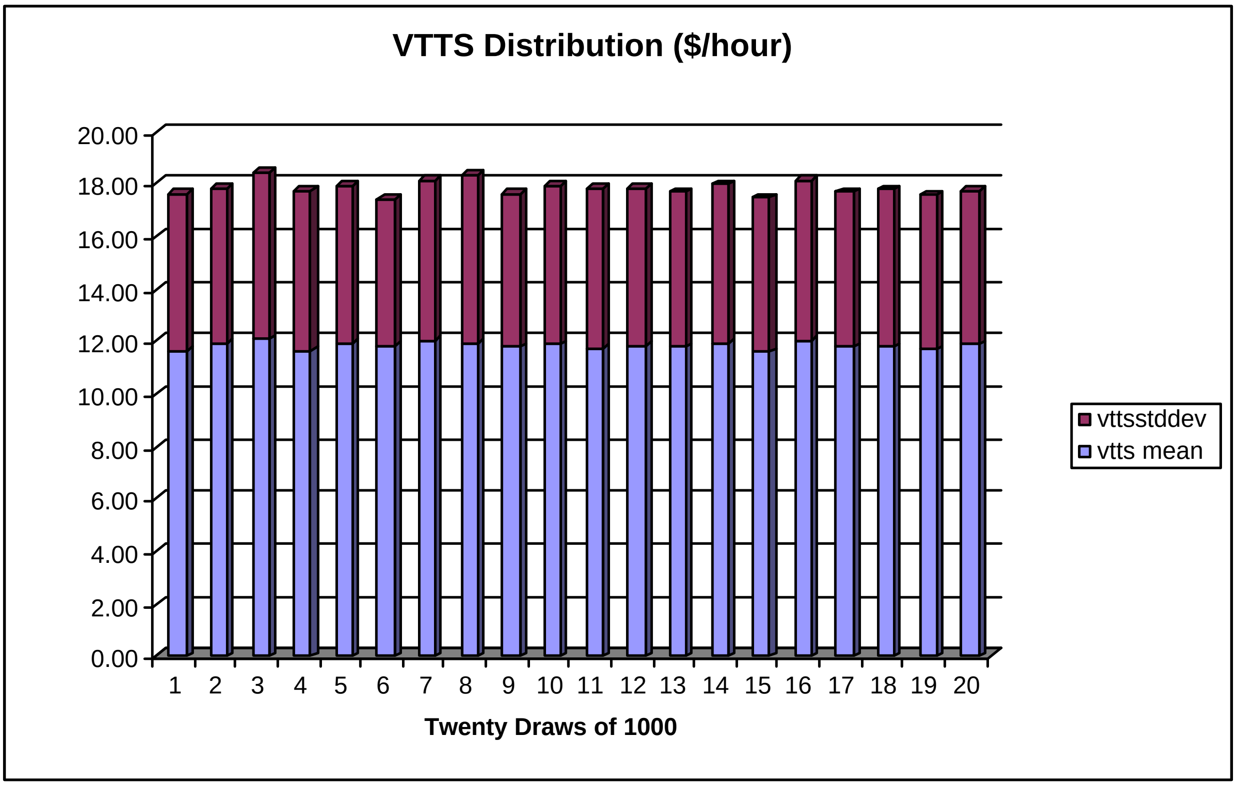


Figure 3 Accommodating Travel Time Valuation Variation

Influence of the Number of Choice Set Treatments

There remains a degree of scepticism in the transport planning community (often unwritten) about the ability of respondents to comprehend and respond to choice designs that involve many alternatives, many attributes and many treatments. Typically, a design with more than two alternatives, three attributes per alternative and four treatments is often perceived as being "too complex" for a respondent. Beesley even suggests this in the quotation above. Analysts frequently ponder on the implications of simplified SP experiments in contrast to statistically more rigorous designs in respect of the goodness-of-fit and the values of travel time savings.

A review of the literature suggests that very little is really known about the basis for rejecting complex designs or accepting simple designs (See Johnson and Orme 1996, Stopher and Hensher 2000). Although it is appreciated that more complex designs provide the analyst with increasing degrees of freedom in the estimation of models, facilitating non-linearity in main effects and independent two-way interactions, it is by no means clear what the overall behavioural gains are to increasing the number of treatments. The question that we focus on is: Are there any statistical and behaviourally substantive differences between the VTTS results from a stated preference model as we vary the number of treatments that are included in model estimation? Holding the set of attributes and choice set size constant, we investigate the implications on mean VTTS of 4, 8, 12 treatments in addition to the 16 treatments reported above.

The findings (for the MNL specification) are summarised in Table 3. We distinguish between an accumulating block strategy (ie estimation using treatments 1-4, 1-8, 1-12 and all 16) and a non-accumulating block strategy (ie treatments 1-4, 5-8, 9-12 and 13-16)[5].

A review of Table 3 suggests the general absence of any obvious relationship between the mean VTTS and the number of treatments in each block strategy. To establish sources of systematic variation in VTTS across the 91 observations in Table 3 (noting that column 1-4 is the same for both block strategies), we investigated the following potential influences: the number of treatments in a block, the accumulating/non-accumulating distinction, the range of the relevant travel time (from both SP and current RP levels), the standard deviation of the travel time attribute, the cost source used in valuation (ie fuel, toll or total) and the t-value of the estimated parameter of each travel time component.

[5] Although the block strategies are based on a single design of 64 rows with four blocks of 16 allocated randomly to each respondent, in contrast to the design of experiments unique to each block strategy, it is unlikely that the loss of orthogonality in all but the 1-16 accumulating block strategy would be a significant contributor to differences in mean VTTS in Table 3. A check of partial correlations showed very little movement in the correlations, supporting empirically that any loss of orthogonality is negligible.

Table 3. Variations in Mean VTTS under Alternative Blocking Strategies

Attribute	Accumulating Block Strategy				Non-Accumulating Block Strategy			
	1-4	1-8	1-12	1-16	1-4	5-8	9-12	13-16
Model 1								
Total time	9.07	9.92	9.71	8.70	9.07	10.66	8.76	4.34
Model 2: fuel cost								
Free flow	7.66	8.96	7.63	5.48	7.66	10.79	3.84 ns	0.36 ns
Slow down	27.63	18.70	20.0	20.3	27.63	13.2	25.62	18.3
Stop/start	30.78	35.45	38.2	40.2	30.78	39.0	40.6	38.6
Uncertainty	6.67	7.79	6.96	7.51	6.67	9.66	5.30ns	5.8ns
Model 2: toll								
Free flow	4.26	5.38	4.71	3.41	4.26	6.38	2.7ns	2.72ns
Slow down	15.36	11.20	12.34	12.62	15.36	7.81	17.7	13.7
Stop/start	17.11	21.3	23.62	25.01	17.11	23.1	28.6	28.9
Uncertainty	3.71	4.66	4.31	4.66	3.71	5.70	3,78ns	4.3ns
Model 3:								
Free flow	4.95	5.85	5.19	3.59	4.95	6.88	3.04ns	0.10ns
Slow down	13.74	11.63	12.91	12.93	13.74	9.82	18.5	13.3
Stop/start	30.93	23.53	25.96	27.80	30.93	26.1	30.7	31.7
Uncertainty	2.61	5.03	4.61	4.98	2.61	7.19	4.02ns	4.4ns

Note: column 1-4 is the same for both blocking strategies.

A series of linear regression models were estimated in which mean VTTS was the dependent variable. The empirical results (see Table 4) find no evidence of any systematic relationship between mean VTTS and the number of treatments in either the accumulating or non-accumulating block strategies (model sets 1-3). There is however very strong evidence that the range of the time attribute (after controlling for time and cost heterogeneity) has a statistically significant influence on mean VTTS, increasing as the range narrows (model set 4). If we impose a range restriction varying from 10% to 100% of the existing range (ie a mean from 14.9 to 298.68 minutes) the mean VTTS across the 91 observations varies from \$20.41 to \$6.92. This is in accordance with a broader finding on the influence of attribute range by Louviere and Hensher (2000). Although there appears to be no 'magic' formula to establish a behaviourally optimal attribute range, Louviere and Hensher (2000) suggest that the wider the range of levels, the more likely it will be that more subjects agree that some levels are "high" whereas others are "low." Thus, the more easily subjects can identify extreme levels, the more likely they are to respond to them more consistently, which reduces within-subject variability (ie greater homogeneity across the treatments for each sampled respondent). Similarly, if more subjects agree that extreme levels are extremes, between-subject variability should decrease (ie there is increased homogeneity within the sample). However, the latter two variance outcomes also can be offset since more extreme levels may induce subjects to behave more extremely, thereby accentuating between-subject differences. The key message is that response variability is a *behavioural phenomenon*, and is an outcome of a choice experiment as much as observed choices and/or model preference parameters or specifications[6].

[6] Failure to recognise that experiments can produce different impacts on the behaviour of random components may lead to misinference, incorrect interpretations and/or possibly even biased results. Hence, it is not possible to optimise choice experiments a priori without also taking the behaviour of the random component into account as an outcome of the design and experiment.

Table 4 Influences on Variability in Mean VTTS

Model Set 1	Estimated parameter	t-value
Accumulating 1-4	-.2085	-.051
Accumulating 1-8	-.6000	-.153
Accumulating 1-12	-.0800	-.019
Constant	13.63	4.5
Adjusted r-squared	-.062	
Model Set 2	Estimated parameter	t-value
Non-Accumulating 1-4	0.612	0.139
Non-Accumulating 5-8	0.752	0.174
Non-Accumulating 9-12	2.05	0.421
Constant	12.81	3.73
Adjusted r-squared	-.058	
Model Set 3	Estimated parameter	t-value
Set 1-4 (accum & non-accum)	0.612	0.139
Accumulating 1-8	0.221	0.052
Accumulating 1-12	0.741	0.167
Accumulating 1-16	0.821	0.179
Non-Accumulating 5-8	0.752	0.174
Non-Accumulating 9-12	2.05	0.421
Constant	12.81	3.73
Adjusted r-squared	-.068	
Model Set 4	Estimated parameter	t-value
Range of attribute (minutes)	-.05105	-2.99
Fuel cost dummy	6.498	6.56
Total cost dummy	1.408	1.90
Free flow time dummy	-6.938	-7.03
Slow down time dummy	-.8776	-.48
Stop-start time dummy	12.11	7.1
Uncertainty dummy	-6.473	-7.5
Constant	19.2058	5.33
Adjusted r-squared	0.901	

Note: except for range of attribute, all other variables are 1,0 dummy variables.

Conclusions

Interest in the measurement of the value of travel time savings continues unabated. Beesley's pioneering research during the 1960's and 70's has contributed to directing the inquiry in a way that has raised our awareness of some significant measurement and specification issues. Some of these have been addressed in this paper. There remains much more to do however. We are seeing major reviews of the current state of empirical practice in a growing number of countries (see Dillen and Algers 1998, Ortuzar 1996, 1996a, Gunn 1996, 2000, Gunn et al 1998, Hensher 1999, Wardman 1998, Accent and Hague Consulting Group 1999, Small et al 1999).

Implicit throughout the contributions of Beesley is recognition of the importance of explaining variance in behavioural response as the overarching theme. This applies as much to the richness of the data in representing real variability as in the ability of models to accommodate all sources of variability, observed and unobserved. The efforts to address this concern during the active writing period by Beesley on VTTS is best summed up in his later papers such as Beesley and Dalvi (1978) where it is noted that

"…despite recent methodological innovations, one point emerges … that very few attempts have been made to improve the accuracy of the results in terms of criteria for homogeneity, the levels of disaggregation or the quality of data. On the other hand, most of the researchers were mainly concerned with the innovation of techniques, ranging from the application of simple classificatory procedures to discriminant and multiple logit models" (page 390).

We can now claim that there is a recognition of the importance of the quality of the data as much as there is a major commitment to specifications of choice models that capture the richer sources of behavioural variability (Louviere and Hensher 2000). This is the Beesley legacy.

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