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TITLE: Extending Valuation to Controlled Value Functions and Non-Uniform Scaling with Generalised Unobserved Variances

ABSTRACT: A common by-product of discrete choice models is the marginal rate of substitution between two attributes (one usually measured in monetary units). The typical output is a point estimate value. In reality there is a distribution of values around a mean which is the product of non-linearities in the role of each attribute in utility space, as well as covariate influences that condition the role of taste weights in dimensioning the relative importance of each attribute in a choice setting. This paper considers the broad issue of breaking away from *valuation* to *valuation functions*, the need to use appropriate experimental design procedures and mean centering or orthogonal codes in estimation with translation back to the real attribute levels in order to reveal the appropriate evaluation distributions. By relaxing the strict constant variance condition in practical discrete choice models, we are able further to absorb unobserved sources of behavioural variability which if not allowed for tend to produce an overvaluation. We illustrate the methods discussed above with a case study on choice of existing and potential commuter modes in six Australian capital cities.

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Introduction

Transportation researchers have progressed our understanding of individual travel behaviour within a set of modelling paradigms of an essentially economic nature, as represented by the rule of utility maximisation. With rare exception, the mainstream empirical emphasis has been on the application of revealed preference (RP) data in a static discrete choice framework with linear additivity assumed for the functional form of the indirect utility expression associated with each alternative in the choice set. In recent years interest has grown in extending the RP data paradigm to incorporate stated choice (SC) data as an enrichment tool in contexts where the attribute levels and choice sets extend beyond the utility space observed in real markets (see Special Issue of Transportation, 1994 as indicative of the state of art). However this extension has stayed essentially within a linear-additive framework and assumed the constant variance assumption of the simple logit model within each of the RP and SC data sub-sets (eg Bradley and Daly 1992, 1994, Hensher and Bradley 1993, Bradley and Gunn 1990, Bradley et al 1996, Morikama 1989, Swait et al 1994, Suzuki et al 1996).

Two restrictions of current practice are the emphasis on deriving marginal rates of substitution between attributes such as the value of travel time savings as *point* estimates rather than as functions, and the *uniform* scaling of RP data when combined with SC data. The constant variance assumption normalises the location parameter which scales the taste weight parameter for each attribute. Relaxing the constant variance assumption enables identification of the unique variances and hence scale parameters associated with each alternative in a choice set. The combined extensions into valuation functions and variable scaling of parameters adds further richness to our understanding of human behavioural response to travel opportunities. A comparison with the traditional logit form highlights the loss of information associated with the more restrictive empirical discrete choice studies.

This paper is organised as follows. The next section discusses the structure of valuation functions and the implications of relaxing the constant variance assumption. In recognising the non-linearity of valuation functions, special consideration must be given to the data form for introducing higher-order attributes such as quadratics and interactions. A series of four discrete choice models are estimated - two basic logit models with constant variance with/without qudtaric and interaction terms for time and cost, and two heteroskedastic logit models with/without quadratic and interaction terms. The distribution of values of travel time savings (VTTS) based on the models with quadratic and interaction terms estimated on a stated choice commuter mode data set for 6 capital cities in Australia are compared between constant and non-constant variance models, highlighting the potential loss of information from the more restrictive assumption. The valuation functions are then applied on revealed preference data from the same sample of commuters to derive a distribution of market-based VTTS, which are used in a classification procedure (CARTS) to segment the commuter market by socioeconoic characteristics with respect to VTTS. Some important implications of using point estimates of VTTS are highlighted.

Valuation Functions Instead of Point Estimates

It is typically assumed that the marginal rates of substitution between any two attributes vary by a number of ‘market segments’ such as mode, trip purpose, trip length and personal income; indeed in the limit we can treat each individual in the sampled population as a segment with unique empirical valuation properties. Within each aggregated market segment, point estimates such as the behavioural value of travel time savings (VTTS) are routinely derived and applied as mean estimates of an unknown (but assumed) distribution. A strictly linear interpretation of the marginal rate of substitution between travel time and travel cost is assumed within the segment. Little understanding of the true profile of VTTS within each segment is known; indeed the set of segment-specific values are treated as threshold values with limited appreciation of the 'best' set of cut-off points if segmented single values are required. For example, VTTS for short, medium and long trips are preconditioned on an exogenous definition of each trip length. Bradley and Gunn (1990), for example, select a series of travel speeds with arbitrary ranges. Whether these arbitrary cut-off points are appropriate or not is not considered. Valuation functions enable us to seek out a continuous distribution of values and to partition this distribution in a more useful way if a set of point estimates are required for practical analysis. Alternatively the richness of the continuous distribution can be preserved and implemented (see Hensher and Truong 1984, Bradley and Gunn 1990).

We propose a distribution of VTTS derived from the non-linearity inherent in the attributes of alternatives (such as travel time and travel cost), and then map these into socio-economic space to identify any systematic variation between VTTS and individual characteristics. This is more appealing and richer than relying on socioeconomic characteristics as both proxies for the non-linearity of travel time and travel cost and the role that socioeconomic characteristics play as proxies for other unobserved influences on choice and hence value. A *value function* is by our definition a functional relationship between VTTS and levels of time and cost both in respect of higher-order (eg quadratic) and interaction (eg two-way product of time and cost). A *segmented valuation function* is a value function conditioned on profiles of characteristics of the individual traveller and/or other external influences.

To begin, assume that the theoretical parameter κ_i from a theoretical indirect utility function of the linear additive form (DeSerpa 1971, Truong and Hensher 1985):

$$V_i = \alpha_i - \lambda C_i - \kappa_i T_i \qquad (1)$$

is a function of C_i and T_i:

$$\kappa_i = \kappa\ (T_i, C_i) \qquad (2)$$

A Taylor series expansion of (2) around the mean levels $\overline{T}$ and $\overline{C}$ for each alternative *i* (neglecting second order terms) results in equation (3).

$$\kappa_i = \overline{\kappa} + (\partial\kappa/\partial T)_i\ (T_i - \overline{T}) + (\partial\kappa/\partial C)_i\ (C_i - \overline{C}) \qquad (3)$$

Substitution of (3) into (1) and some rearrangement of terms gives:

$$V = \alpha_i - \lambda C_i - \overline{\kappa} T_i + (\beta T_i^2 + \gamma C_i T_i + \omega) \qquad (4)$$

where

$\beta = (\partial\kappa/\partial T)_i$, $\gamma = (\partial\kappa/\partial C)_i$, and $\omega = -\beta\overline{T} - \gamma\overline{C}$.

By neglecting second-order terms in (3) we implied that $\partial\kappa/\partial T$ and $\partial\kappa/\partial C$ are constants, independent of alternative i. Equivalently, the parameters ω, β and γ are unsubscripted. The VTTS can now be derived from (4) as follows (Hensher and Truong 1985, Hensher 1995):

$$\text{VTTS} = \frac{\partial V/\partial T_i}{\partial V/\partial C_i} \Big| V_i = \text{constant}$$

$$= \frac{-\bar{\kappa} + \gamma C_i + 2\beta T_i}{-\lambda + \gamma T_i} \tag{5}$$

Thus VTTS is dependent on the levels of travel time and cost. This formula can be generalised to account for the disaggregation of travel time (see Hensher and Truong (1985) for more details). We can introduce interactions between each travel time and between travel time and other attributes of alternatives. The ability to enrich the valuation function to test for a richer specification is conditioned by the quality of data.

Revealed preference data is usually somewhat limiting in its ability to offer sufficient richness in both variability and correlation structure to enable each potential influence to be included without producing confoundment. This is particularly true when accounting for non-linearity and when 'new' alternatives are assessed for market share. Data derived from a stated choice experiment however increases the opportunity to account for the independent (ie additive) contribution of each source of variability in the valuation function in an expanded choice set. It is for this reason, amongst other reasons, that the stated choice paradigm has evolved to become an important feature of a preferred empirical approach to obtaining behavioural values of travel time savings (see Bradley et al 1996).

Developing a Valuation Function

To identify the underlying structure of a stated choice experiment, and to understand how the valuation function is derived from the information in this experiment, we begin by defining the information potential of each attribute to be evaluated in the choice experiment. Assume that each attribute in a mode choice experiment has three levels, represented two ways - as nominal or mean centred values (-1, 0, 1) or as actual levels (eg \$1, \$2 and \$3). The non-linearity of an attribute can be accounted for by specifying higher order dimensions such as quadratics. A three-level attribute contains information up to the quadratic dimension (or order two). A quadratic term is constructed by squaring the value of the attribute and replacing the nominal mid-point (0) with the nominal -2.

Let v(X) denote the marginal utility which arises from attribute X alone (e.g. travel time or cost). If v(X) is non-linear in X, a second-order polynomial approximation for v(X) can be written as

$$v(X) = \alpha X + \beta X^2 \tag{6}$$

We can derive relationships between v(X) and X that show the role of the quadratic term and why it is important to be able to test for non linearity by separating out the independent contribution of X^2, and hence determining if both X and X^2 are required to capture the full effect due to attribute X (given the limiting assumption of a maximum order 2 with only 3 levels of an attribute) (Hensher 1995).

$$\alpha = (v_3 - v_2)/2 \quad (7)$$
$$\beta = [(v_3 - v2) - (v_2 - v_1)]/6 \quad (8)$$

where α measures the mean slope between X = -1 and X = 1; and β measures the change in slope between (X = -1, X = 0) and (X = 0, X = 1).

In addition to the non-linearity of each attribute's influence on the value of travel time savings (equation 5), the possibility of two-way interactions between pairs of attributes needs to be considered. In fractional factorial designs the number of two-way interactions which are independent (i.e orthogonal) from the main effects (i.e. X and X^2) are determined by the actual fraction selected and the degrees of freedom ensuing from the design. For VTTS functions, we are interested in the interaction between travel cost and travel time. With a quadratic term in the main effect for travel time and one interaction term for cost and time, we are able to evaluate the empirical form of the valuation function. A valuation function arises from a specification that includes quadratic and/or interaction terms.

Since the quadratic of an orthogonally coded nominal attribute is not equivalent to the quadratic of the actual value of an attribute, we require a mapping from one metric to the other. We estimate the logit model using the orthogonal codes but determine the value of travel time savings based on the actual levels of the attributes shown to the sampled population.

Define the nominal level as N and the actual level as A. For a three-level attribute, define:

$$N = \theta_0 + \theta_1 A \quad (9)$$

$$N^2 = \delta_0 + \delta_1 A + \delta_2 A^2 \quad (10)$$

Denote the three levels for A as low (L), medium (M) and high (H) and L^2, M^2 and H^2 for A^2. Given the orthogonal codes for N (-1, 0, 1) and N^2 (1, -2, 1), substitution into equations (9) and (10) gives the following transformation functions:

$$-1 = \theta_0 + \theta_1 L \quad (11)$$
$$0 = \theta_0 + \theta_1 M \quad (12)$$
$$1 = \theta_0 + \theta_1 H \quad (13)$$

where $\theta_1 = 1/\Delta_i$, $\theta_0 = -M/\Delta_i$, and $\Delta_i = M - L = H - M$ (assuming equal spacing for attribute i), and

$$1 = \delta_0 + \delta_1 L + \delta_2 L^2 \quad (14)$$
$$-2 = \delta_0 + \delta_1 M + \delta_2 M^2 \quad (15)$$
$$1 = \delta_0 + \delta_1 H + \delta_2 H^2 \quad (16)$$

and $\delta_2 = 3/\Delta_i^2$, $\delta_1 = -6M/\Delta_i^2$, and $\delta_0 = -2 + 3M^2/\Delta_i^2$.

The utility expression associated with each alternative as estimated using nominal attribute levels can be specified as:

$$V_i = \eta + \eta_1 C + \eta_2 T + \eta_3 T^2 + \eta_4 CT \quad (17)$$

They can be translated from nominal to actual levels of attributes as follows:

$$V_i = \omega + \omega_1 c + \omega_2 t + \omega_3 t^2 + \omega_4 ct \quad (18)$$

Defining M_i as the actual mean level of attribute *i* and Δ_i as the step change in the level of attribute *i*, we derive the following conversion relationships:

$$\omega_1 = [\eta_1/\Delta_c - M_t\eta_4/(\Delta_c\Delta_t)] \quad (19)$$

$$\omega_2 = [\eta_2/\Delta_t - 6M_t\eta_3/\Delta_t^2 - M_c\eta_4/(\Delta_c\Delta_t)] \quad (20)$$

$$\omega_3 = [3\eta_3/\Delta_t^2] \quad (21)$$

$$\omega_4 = [\eta_4/\Delta_c\Delta_t] \quad (22)$$

Relaxing the Constant Variance Assumption

Each attribute in the indirect utility expression associated with an alternative has a beta parameter identifying its contribution to variation in the level of relative utility which is the product of two components - a location or scale parameter and a taste weight parameter. In the simple logit form with constant variance in the unobserved effects, it is well known that the scale parameter, as an index of variability in the unobserved effects, can be arbitrarily set equal to one. When the interest centres on valuation, the ratio of any two or more attributes within the utility expression for a single alternative cancels the scale effect. However the simple logit form assumes that this constant scalar is independent of the alternatives in the choice set and hence has no effect on comparing values *across* alternatives (McFadden 1981). Assuming uniqueness may be unsatisfactory. If the scale parameters vary between alternatives then the relative valuation between alternatives will be distorted. The extent is unknown and is essentially empirical (Bhat 1995). This, however, is an important issue since we should be interested in both the *absolute* values *and* the *relative* values. For example, if there are noticeable unobserved effects with high variance associated with the public transport alternatives in contrast to the automobile alternatives, then the constant variance assumption can overvalue the VTTS for public transport use relative to automobile use.

To relax the constant variance assumption requires a more complex choice model, called the heteroscedastic extreme value logit (HEVL) model. Allemby and Glinter (1995) and Bhat (1995) have recently implemented the HEVL model on revealed preference data, but have not considered the benefits of the HEVL specification for relative valuation.

Define the behavioural choice rule as

$$P_i = \text{Prob}[U_i > U_j] \text{ for all j not equal to I} \quad (23)$$

$$= \int_{-\infty}^{+\infty} \pi(j \neq i)\ F(\lambda_j)\{V_i - V_j + \varepsilon_i\}]\lambda_i f[\lambda_i \varepsilon_i] d\varepsilon_i \qquad (24$$

where f(t) is the density function, f(t) = exp(-t)*exp(-exp(-t)) = -F(t)*log(F(t)). The probabilities are evaluated numerically as there is no closed-form solution for the integral. The scale parameter is $\frac{1}{\lambda}$, where the square of lambda is proportional to the inverse of the variance of the unobserved random component of utility, ε_i. The integral can be approximated using Gauss-Laguerre quadrature (Bhat 1995). Thus we can replace equation (23) with equation (24), where w is the weight and z(l) is the abscissa of the Gauss-Laguerre polynomial. A 12 point approximation has proven sufficient (Greene 1996). The derivatives can be used in constructing the log-likelihood and for calculation of the full matrix of direct and cross share elasticities.

$$\int_{-\infty}^{+\infty} \pi(j \neq i)\ F[t(j|i)]\ \exp[-u(i)]\ du(i) \approx \Sigma(l)\ w(l)\ F(z(l)) \qquad (25$$

Specification of an Empirical Inquiry to Evaluate the Benefits of Generalisation

As part of a study investigating the impact of transport policy instruments on reductions in greenhouse gas emissions in six Australian capital cities - Sydney, Melbourne, Brisbane, Adelaide, Perth and Canberra (Hensher et al 1995), a stated choice experiment centred on commuter mode choice was designed (Louviere et. al 1994). The universal choice set comprised the currently available modes plus two ‘new’ modes - light rail and busway.

Each respondent considered a context in which the offered set of attributes and levels represent the available ways of undertaking a commuter trip from the current residential location to the current workplace location. The purpose is to establish their coping strategies under these circumstances. Four alternatives appear in each travel choice scenario - car (no toll), car (toll), bus or busway, and train or light rail. There are 12 types of showcards, with three trip lengths and four combinations of public transport: bus vs. light rail, bus vs. train (heavy rail), busway vs. light rail, and busway vs. train. The public transport combinations appear in each showcard with incidence determined by the statistical design. The range of attribute levels are summarised in Table 1; the contextual statement is given in Appendix A together with an illustrative showcard.

The five attributes for the public transport alternatives are total in-vehicle time, frequency of service, closest stop to home, closest stop to destination, and fare. The attributes for the car alternatives are travel time, fuel cost, parking cost, travel time variability, and for the toll road - departure time and toll charge. Three levels were selected for each attribute. Detailed definitions of each attribute are given in Appendix B. The design allows for six alternative-specific main effect models for car no toll, car toll road, bus, busway, train, and light rail. Linear by linear interactions are estimable for both car models, and generically for the bus/busway and train/light rail models. While cross effects have been assumed negligible, the four-alternative design is perfectly balanced across all attributes. The design has been blocked into 27 versions of size three also balanced for every attribute such that each respondent sees each level of each attribute exactly one time.

Table 1. **The Set of Attributes and Attribute Levels in the Travel Choice Experiment**
(all cost items are in $'s, all time items are in minutes)

SHORT (< 30 mins.)	Car no toll	Car toll road	PUBLIC TRANSPORT	Bus	Train	Busway	Light Rail
Travel time to work	15,20,25	10,12,15	Total time in the vehicle (one-way)	10,15,20	10,15,20	10,15,20	10,15,20
Pay toll if you leave at this time (otherwise free)	None	6-10, 6:30-8:30, 6:30-9	Frequency of service	Every 5,15,25	Every 5,15,25	Every 5,15,25	Every 5,15,25
Toll (one-way)	None	1,1.5,2	Time from home to your closest stop	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8
Fuel cost (per day)	3,4,5	1,2,3	Time to your destination from the closest stop	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8
Parking cost (per day)	Free,$10,$20	Free,$10,$20	Return fare	1,3,5	1,3,5	1,3,5	1,3,5
Time variability	0, ±4,±6	0,±1,±2					
MEDIUM (30-45 mins.)							
Travel time to work	30,37,45	20,25,30	Total time in the vehicle (one-way)	20,25,30	20,25,30	20,25,30	20,25,30
Pay toll if you leave at this time (otherwise free)	None	6-10, 6:30-8:30, 6:30-9	Frequency of service	Every 5,15,25	Every 5,15,25	Every 5,15,25	Every 5,15,25
Toll (one-way)	None	2,3,4	Time from home to your closest stop	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8
Fuel cost (per day)	6,8,10	2,4,6	Time to your destination from the closest stop	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8
Parking cost (per day)	Free,$10,$20	Free,$10,$20	Return fare	2,4,6	2,4,6	2,4,6	2,4,6
Time variability	0, ±7, ±11	0, ±2, ±4					
LONG (>45 mins.)							
Travel time to work	45,55,70	30,37,45	Total time in the vehicle (one-way)	30,35,40	30,35,40	30,35,40	30,35,40
Pay toll if you leave at this time (otherwise free)	None	6-10, 6:30-8:30, 6:30-9	Frequency of service	Every 5,15,25	Every 5,15,25	Every 5,15,25	Every 5,15,25
Toll (one-way)	None	3,4.5,6	Time from home to your closest stop	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8	Walk 5,15,25 Car/Bus 4,6,8
Fuel cost (per day)	9,12,15	3,6,9	Time to your destination from the closest stop	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8	Walk 5,15,25 Bus 4,6,8
Parking cost (per day)	Free,$10,$20	Free,$10,$20	Return fare	3,5,7	3,5,7	3,5,7	3,5,7
Time variability	0, ±11, ±17	0, ±7, ±11					

The base design for the travel choice task was a 27 x 327 orthogonal fractional factorial in 81 runs. The 27 level factor was used for creating the versions, and the three level factors selected and arranged to meet the design requirements. Two factors each at two levels were constructed for the bus/busway and train/light rail modes. In the design, bus and train appear in 36 scenarios while busway and light rail appear in 45.

Empirical Results

Four mode choice models have been estimated as the basis for deriving a valuation function in the presence and absence of constant variance in the unobserved effects. The four models are:

Basic logit model (BL), Heteroscedastic extreme value logit model (HEVL), Basic non-linear logit model (BnlL) and Heteroscedastic extreme value non-linear logit model(HEVnlL). Model estimation is limited to only two car design attributes (fuel and time) and four public transport attributes (fare, main mode time, access time and egress time). The car alternatives have been pooled across toll and no toll and segmented by drive alone and ride share.

A profile of the data set is given in Table 2, with full model results in Tables 3-6. A direct comparison of all four models is not informative - rather we need to consider the derivative outputs in the form of values of travel time savings. Two models produce point estimates of VTTS for each mode (ie BL, HEVL); two models provide valuation functions for VTTS (ie BnlL, HEVnlL), and two models provide point estimates of direct and cross share elasticities (ie BL, HEVL). The BnlL and HEVnl can be applied to obtain a distribution of share elasticities as a function of price and time, but we do not report them here. It is sufficient to compare the point estimates of weighted aggregate elasticities to establish the potential loss of information from a constant location scale parameter.

Table 2. **Stated choice profile: means and proportions for each attribute in base model**

Attribute	Drive Alone	Ride Share	Bus	Train	Light rail	Busway
In choice set	2016	2016	902	889	1127	1114
Chosen	559	325	252	235	340	305
Mode shares	.277	.161	.125	.117	.168	.151
One-way fuel/fare cost ($)	2.815	2.815	1.784	1.769	1.776	1.766
Main mode time (mins.)	27.794	27.794	18.359	20.332	20.546	18.456
Access time (mins.)	-	-	11.032	11.965	11.827	10.764
Egress time (mins.)	-	-	11.062	12.120	12.068	11.048
Daily parking cost ($)	8.507	8.507	-			
Personal income ($000s)	33.487	-	-			
Car availability index	1.090	-	-			

Note: car availability index is defined as the ratio of number of cars in household to number of workers.

The overall goodness of fit of the model set varies from 0.32 to 0.38. The valuation function models are more complex and produce a slightly smaller reductions in the log-likelihood towards zero at convergence. The additional attributes introduced into the valuation function models vary in significance across the six modal alternatives. The quadratic in time contributes to the bus and light rail modes but with opposite signs. A negative sign suggests that the rate of change in relative utility associated with a travel time increase decreases at an increasing rate as travel time increases. A positive sign suggests that the rate of change in relative utility associated with a travel time increase decreases at an decreasing rate as travel time increases. The two-way interactions between time and price are statistically significant in drive alone and ride share (positive), and in train and busway (negative). A positive sign indicates that, as travel time increases, the change in relative utility is less as price increases. A negative sign indicates that, as travel time increases, the change in relative utility is greater as price increases.

Table 3. **Base Stated Choice Model: Simple Logit for 6 cities (5 iterations)**

Attribute	Alternative(s)	Acronym	Estimate	T-value
Drive alone constant	DA	DASC	.39918	1.22
In-vehicle cost	All	CST	-.55209	-13.73
Main mode time	DA, RS	TMCAR	-.059778	-10.00
Parking cost (all day)	DA,RS	PRK	-.09745	-13.71
Personal income	DA	PINC	.00784	2.39
Car availability index	DA	CARAV	.34451	3.80
Ride share constant	RS	RSASC	.51850	2.82
Bus specific constant	BS	BSASC	.051506	0.46
Main mode time	BS,TN,LR,BWY	TMPT	-.069077	-9.38
Access mode time	BS,TN,LR,BWY	ACT	-.04253	-7.53
Egress mode time	BS,TN,LR,BWY	EGT	-.020825	-3.74
Train specific constant	TN	TNASC	.23524	2.22
Light rail specific constant	LR	LRASC	.32225	3.40
Log-likelihood at convergence	-2241.16			
Pseudo-R^2	0.37			

Table 4. **Basic Stated Choice Model: HEV Logit for 6 cities (70 iterations)**

Attribute	Alternative(s)	Acronym	Estimate	T-value
Drive alone constant	DA	DASC	1.7449	19.71
In-vehicle cost	All	CST	-.051265	-3.60
Main mode time	DA, RS	TMCAR	-.005719	-3.35
Parking cost (all day)	DA	PRK	-.013878	-3.45
Personal income	DA	PINC	.0016314	2.14
Car availability index	DA	CARAV	.062650	2.45
Ride share constant	RS	RSASC	1.7054	17.97
Bus specific constant	BS	BSASC	1.7981	27.09
Main mode time	BS,TN,LR,BWY	TMPT	-.00294	-2.61
Access mode time	BS,TN,LR,BWY	ACT	-.003857	-2.95
Egress mode time	BS,TN,LR,BWY	EGT	-.000818	-1.44
Train specific constant	TN	TNASC	1.7692	22.79
Light rail specific constant	LR	LRASC	1.7691	24.17
Lambda	DA		4.3109	3.29
Lambda	RS		4.0631	3.34
Lambda	BS		17.357	3.76
Lambda	TN		9.2403	2.90
Lambda	LR		10.107	3.80
Lambda	BWY		1.000	-
Log-likelihood at convergence	-2467.96			
Pseudo-R^2	0.315			

Table 5. **Valuation Function Stated Choice Model: Basic Logit for 6 cities (6 iterations)**

Attribute	Alternative(s)	Acronym	Estimate	T-value
Drive alone constant	DA	DASC	-.344484	-3.29
In-vehicle cost	All	CST	-.57166	-14.15
Main mode time	DA, RS	TMCAR	-.068657	-10.86
Parking cost (all day)	DA	PRK	-.097506	-13.54
Personal income	DA	PINC	.007868	2.39
Car availability index	DA	CARAV	.35052	3.83
Ride share constant	RS	RSASC	-.80128	-6.99
Bus specific constant	BS	BSASC	.16340	1.28
Main mode time	BS,TN,LR,BWY	TMPT	.060689	-8.08
Access mode time	BS,TN,LR,BWY	ACT	-.042895	-7.5
Egress mode time	BS,TN,LR,BWY	EGT	-.020764	-3.70
Train specific constant	TN	TNASC	.028564	0.26
Light rail specific constant	LR	LRASC	-.01880	-.16
Quadratic time	BS	TMPTQB	-.002184	-2.69
Quadratic time	LR	TMPTQL	.0009425	1.65
Interactive time and cost	DA	TCMDA	.012865	4.73
Interactive time and cost	RS	TCMRS	.009216	2.66
Interactive time and cost	TN	TCMPT	-.016104	-1.51
Interactive time and cost	BWY	TCMPTW	-.014921	-1.68
Log-likelihood at convergence	-2239.67			
Pseudo-R^2	0.38			

Table 6. **Valuation Function Stated Choice Model: HEV Logit for 6 cities (114 iterations)**

Attribute	Alternative(s)	Acronym	Estimate	T-value
Drive alone constant	DA	DASC	1.7707	7.45
In-vehicle cost	All	CST	-.05765	-1.04
Main mode time	DA, RS	TMCAR	-.006877	-1.43
Parking cost (all day)	DA	PRK	-.008829	-1.53
Personal income	DA	PINC	.0005549	1.4
Car availability index	DA	CARAV	.052777	1.6
Ride share constant	RS	RSASC	-.03264	-.05
Bus specific constant	BS	BSASC	1.7904	8.19
Main mode time	BS,TN,LR,BWY	TMPT	-.007243	-1.53
Access mode time	BS,TN,LR,BWY	ACT	-.004343	-1.76
Egress mode time	BS,TN,LR,BWY	EGT	-.0018195	-1.54
Train specific constant	TN	TNASC	1.7993	8.60
Light rail specific constant	LR	LRASC	1.7884	8.11
Lambda	DA		9.4223	1.32
Lambda	RS		.9783	1.75
Lambda	BS		7.7896	1.43
Lambda	TN		9.4361	1.54
Lambda	LR		9.3416	1.76
Lambda	BWY		1.000	-
Quadratic time	BS	TMPTQB	-.0002086	-1.53
Quadratic time	LR	TMPTQL	.00006717	1.83
Interactive time and cost	DA	TCMDA	.001289	1.32
Interactive time and cost	RS	TCMRS	.0003655	1.42
Interactive time and cost	TN	TCMPT	-.002344	-1.78
Interactive time and cost	BWY	TCMPTW	.0004882	1.03

Log-likelihood at convergence	-2301.06
Pseudo-R^2	.360

Table 7. **Mean Estimates of Commuter Values of Travel Time Savings ($ per person hour)** note: * columns are based on mean time and cost from Table 1

	BL	HEVL	BnlL *	HEVnlL *
Drive Alone	6.50	6.69	7.21	7.12
Ride Share	6.50	6.69	7.21	7.12
Bus	7.51	3.44	6.37	7.54
Train	7.51	3.44	6.37	7.54
Light Rail	7.51	3.44	6.37	7.54
Busway	7.51	3.44	6.37	7.54

An important result emerges from a comparison of the BL and HEVL models. The mean VTTS for public transport is substantially lower when we relax the constant variance assumption. In contrast the mean VTTS for drive alone and ride share is slightly higher. The reasoning lies in the variance estimates. The mean estimate of variance varies substantially across the four public transport modes, given busway is set equal with 1.00. The large variance associated with unobserved effects which clearly are more prominent for public transport appear to have confounded the contribution of time and cost in public transport more than for the automobile. Consequently the inflated VTTS for public transport in the basic logit model is the result of failure to account for some unobserved influences on relative utility which are suppressed through the constant variance assumption and consequently 'distributed' to the observed effects. However when we introduce non-linearity into the VTTS estimate expressed as a valuation function we find that at the mean of the sample travel time and costs that the higher VTTS associated with the basic linear model is 'reinstated' for public transport. The fact that we have a similar value at the mean of the sample for HEVnlL does not imply that the basic linear model is 'correct'; rather it suggests in this single empirical study that the downward valuation for public transport VTTS consequent on allowing for non-constant variance in a linear specification is approximately offset by an upward valuation after allowing for non-linearity in the non-constant variance model, producing a result at the sample mean very close to that of a constant variance model with linearity. What is of more importance is the distribution of values across the sample summarised in Table 8 for a range of travel times and costs for each of the 6 modes.

Empirical Valuation Functions

There are two empirical forms of equation (5), the VTTS function. For drive alone, ride share, train and busway we have:

$$VTTS_{(DA,RS,TN,BWY)} = \frac{\beta + \eta C}{\alpha + \eta T} \quad (25$$

For bus and light rail we have:

$$VTTS_{(BS,LR)} = \frac{\beta + 2\gamma T}{\alpha} \quad (26$$

where

β = linear time parameter

γ = quadratic time parameter
η = interaction of time and cost parameter
α = linear cost parameter
C and T are nominal levels.

The range of VTTS BnlL and HEVnlL in Table 9 may appear to be similar, but in fact the differences are quite substantial, especially for public transport. The only mode with consistently similar VTTS is car drive alone. For the other modes, the difference can be as high as 90%, with the HEVnlL model producing higher VTTS. The implications for forecasts of user benefits in transport project evaluation is clear - there is the potential for substantial differences in the net benefits to different segments of the travelling market; currently simple mean point estimates have the following properties in the current study: they over-estimate the time benefits for, train, light-rail and busway trips, and under-estimate them for the shorter train trips, longer car drive alone and bus trips. These findings translate to the distribution of VTTS by mode derived from distributions of actual market times and costs (see below).

Table 8. **VTTS distribution in travel time and cost space for each commuter mode based a synthesised range of times and costs - BnlL model (HEVnlL in parenthesis)**

	DA	RS	BS	TN	LR	BWY
c=1, t=20	8.22 (8.25)	7.96 (7.56)	7.12 (8.34)	5.12 (5.81)	6.48 (7.70)	4.97 (8.13)
c=1, t=25	9.09 (9.13)	8.58 (7.80)	9.41 (10.54)	4.48 (4.80)	5.49 (6.99)	4.42 (8.49)
c=1, t=30	10.16 (10.21)	9.29 (8.05)	11.71 (12.74)	3.98 (4.10)	4.50 (6.29)	3.97 (8.90)
c=1, t=35	11.53 (11.59)	10.14 (8.32)	14.00 (14.93)	3.59 (3.57)	3.51 (5.58)	3.61 (9.34)
c=1, t=40	13.31 (13.40)	11.16 (8.61)	16.29 (17.13)	3.26 (3.17)	2.52 (4.87)	3.31 (9.83)
c=1.5, t=20	7.64 (7.67)	7.53 (7.38)	7.12 (8.34)	5.97 (7.06)	6.48 (7.70)	5.72 (7.86)
c=1.5, t=25	8.45 (8.49)	8.11 (7.61)	9.41 (10.54)	5.23 (5.84)	5.49 (6.99)	5.08 (8.22)
c=1.5, t=30	9.45 (9.50)	8.79 (7.86)	11.71 (12.74)	4.65 (4.98)	4.50 (6.29)	4.57 (8.61)
c=1.5, t=35	10.72 (10.78)	9.59 (8.12)	14.00 (14.93)	4.19 (4.34)	3.51 (5.58)	4.16 (9.04)
c=1.5, t=40	12.38 (12.46)	10.56 (8.40)	16.29 (17.13)	3.81 (3.85)	2.52 (4.87)	3.81 (9.52)
c=2, t=20	7.07 (7.09)	7.10 (7.19)	7.12 (8.34)	6.82 (8.31)	6.48 (7.70)	6.48 (7.60)
c=2, t=25	7.82 (7.85)	7.65 (7.42)	9.41 (10.54)	5.97 (6.87)	5.49 (6.99)	5.75 (7.95)
c=2, t=30	8.74 (8.78)	8.29 (7.66)	11.71 (12.74)	5.31 (5.86)	4.50 (6.29)	5.18 (8.33)
c=2, t=35	9.91 (9.97)	9.05 (7.92)	14.00 (14.93)	4.78 (5.11)	3.51 (5.58)	4.70 (8.74)
c=2, t=40	11.45 (11.53)	9.95 (8.19)	16.29 (17.13)	4.35 (4.53)	2.52 (4.87)	4.31 (9.20)
c=2.5, t=20	6.49 (6.52)	6.67 (7.01)	7.12 (8.34)	7.68 (9.56)	6.48 (7.70)	7.23 (7.34)
c=2.5, t=25	7.18 (7.21)	7.19 (7.23)	9.41 (10.54)	6.72 (7.91)	5.49 (6.99)	6.42 (7.68)
c=2.5, t=30	8.03 (8.07)	7.79 (7.47)	11.71 (12.74)	5.98 (6.75)	4.50 (6.29)	5.78 (8.04)
c=2.5, t=35	9.11 (9.16)	8.50 (7.72)	14.00 (14.93)	5.38 (5.88)	3.51 (5.58)	5.25 (8.44)
c=2.5, t=40	10.52 (10.59)	9.35 (7.99)	16.29 (17.13)	4.89 (5.21)	2.52 (4.87)	4.81 (8.89)
c=3, t=20	5.92 (5.94)	6.24 (6.83)	7.12 (8.34)	8.53 (10.81)	6.48 (7.70)	7.98 (7.08)
c=3, t=25	6.54 (6.57)	6.72 (7.04)	9.41 (10.54)	7.47 (8.94)	5.49 (6.99)	7.09 (7.41)
c=3, t=30	7.32 (7.35)	7.29 (7.27)	11.71 (12.74)	6.64 (7.63)	4.50 (6.29)	6.38 (7.76)
c=3, t=35	8.30 (8.35)	7.95 (7.52)	14.00 (14.93)	5.98 (6.65)	3.51 (5.58)	5.80 (8.14)
c=3, t=40	9.59 (9.65)	8.75 (7.78)	16.29 (17.13)	5.44 (5.89)	2.52 (4.87)	5.31 (8.57)
c=3.5, t=20	5.34 (5.36)	5.81 (6.64)	7.12 (8.34)	9.38 (12.06)	6.48 (7.70)	8.73 (6.82)
c=3.5, t=25	5.91 (5.93)	6.26 (6.85)	9.41 (10.54)	8.22 (9.98)	5.49 (6.99)	7.76 (7.13)
c=3.5, t=30	6.61 (6.64)	6.78 (7.08)	11.71 (12.74)	7.31 (8.51)	4.50 (6.29)	6.98 (7.47)
c=3.5, t=35	7.50 (7.54)	7.40 (7.31)	14.00 (14.93)	6.58 (7.42)	3.51 (5.58)	6.35 (7.84)
c=3.5, t=40	8.66 (8.72)	8.15 (7.57)	16.29 (17.13)	5.98 (6.58)	2.52 (4.87)	5.82 (8.26)
Range:						
BnlL	5.34 - 13.31	5.81 - 11.16	7.12 - 16.29	3.26 - 9.38	2.52 - 6.48	3.31 - 8.73

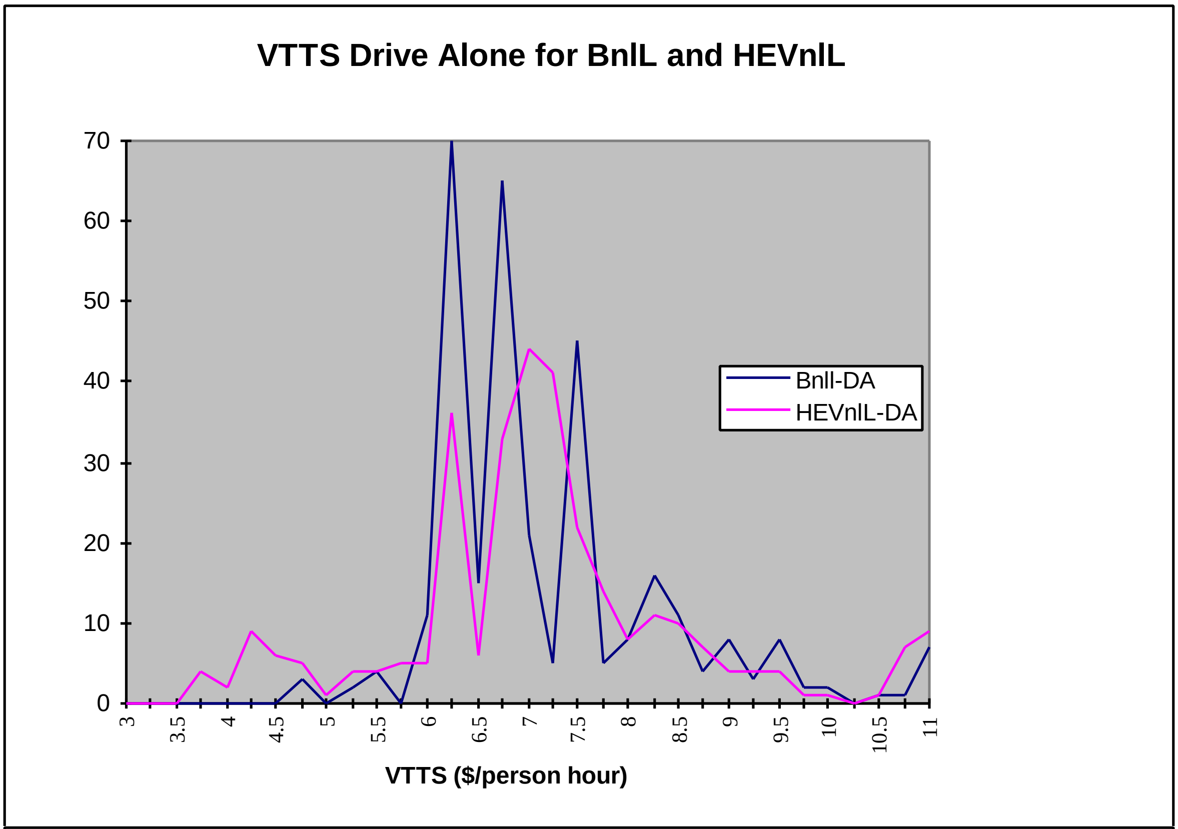
HEVnlL	5.36 - 13.40	6.64 - 8.61	8.34 - 17.13	3.17 - 12.06	4.87 - 7.70	6.83 - 9.83

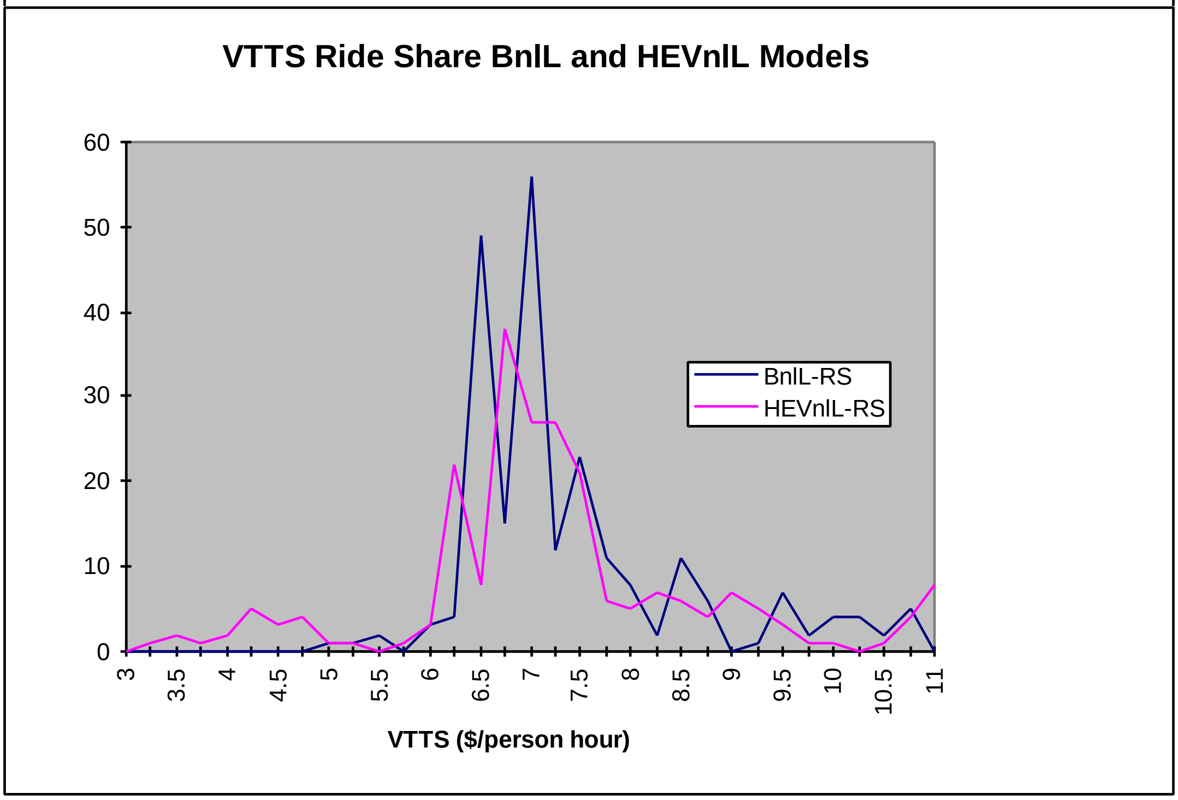
Mapping Valuation Function Outputs with Socioeconomic Segments

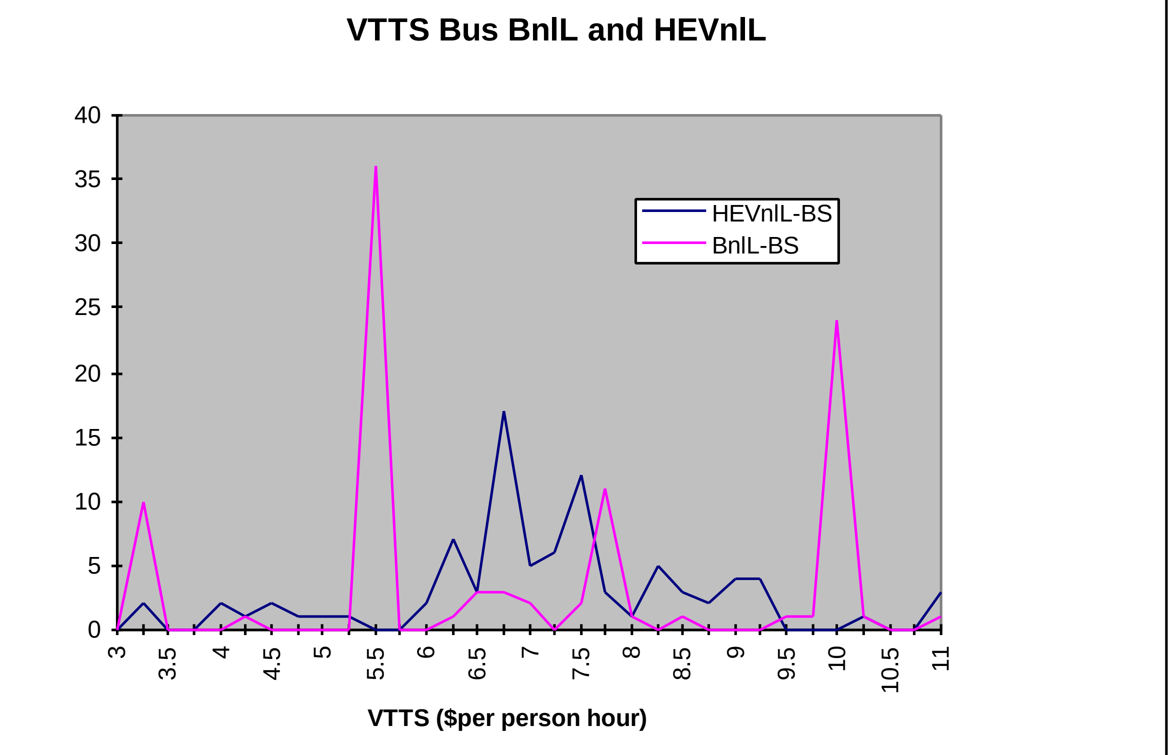
To meaningfully evaluate the relationship between VTTS and socioeconomic characteristics of the commuter and their household, we derived VTTS for each sampled commuter for each alternative in their choice set for both BnlL and HEVnlL models (Figures 1-4). We then implemented a method known as CARTS (classification and regression trees - Breiman et al 1993) to partition the data into relatively homogeneous terminal nodes (ie classes), taking the mean value of VTTS observed in each node as its predicted value. The mean square error is used to rank trees of different sizes. In addition a resubstitution relative cost measure is generated to measure the misclassification rate for the data used to grow the classification tree. After extensive testing we were able to establish the role of socio-economic characteristics in partitioning the sample, namely age of commuter, personal income and car availability. A simple linear generalised least squares regression confimed the statistical significance of these three influences on variation in VTTS across the sampled population. Other socioeconomic variables - occupation, employment status, sex, city of residence, drivers licence status and highest level of education had no significant influence at all.

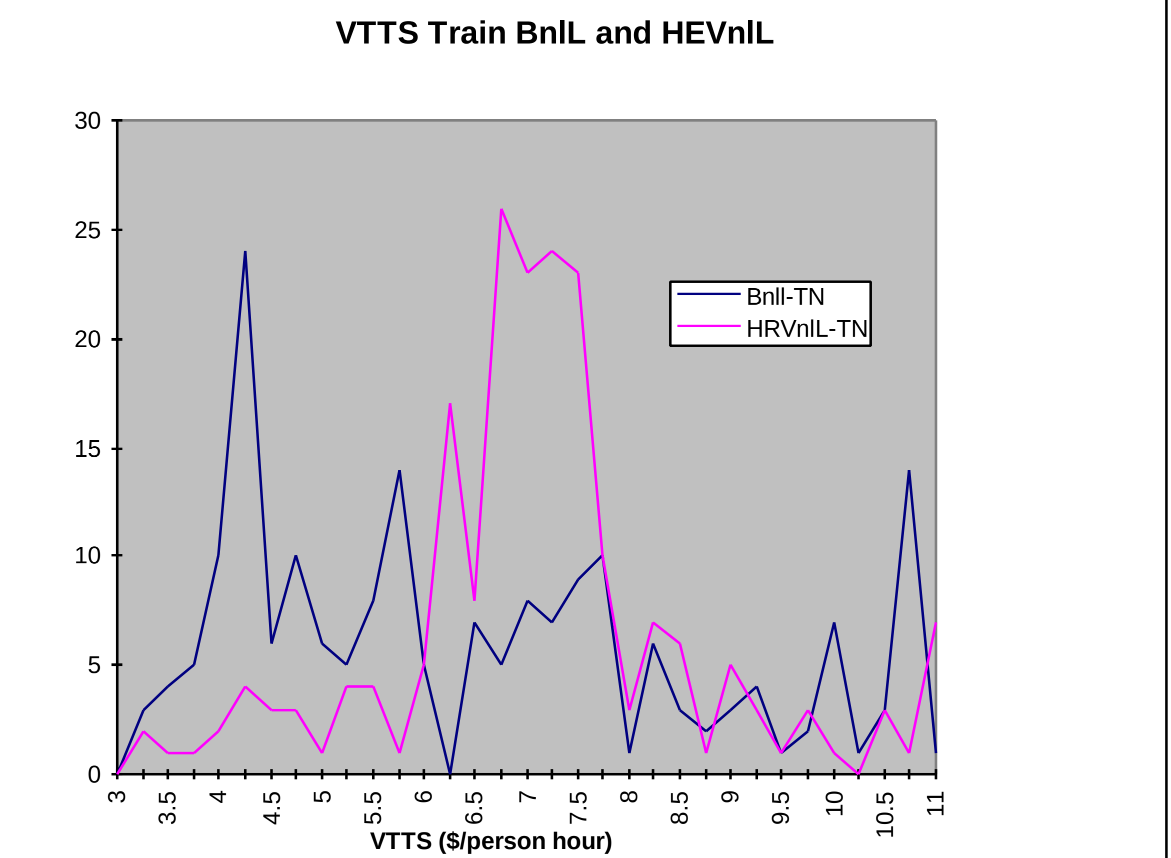
The VTTS for all modes were pooled in the CARTS analysis for each of BnlL and HEVnlL derived VTTS. The BnlL analysis produced 17 nodes and the HEVnlL analysis produced 21 nodes, in both cases at a depth of 5 (ie a 5-level tree). Age of the commuter, followed by car availability and then personal income defines the relative importance of socio-economic discrimination in the two analyses. The concept of important in a CART application involves calculation of the improvement measure attributble to each socio-economic variable in its role as a surrogate to the primary split. The value of these improvements are summed over each node and totalled, and then scaled relative to the best performing variable. The most important variable, age, is given an importance score of 100 in both analyses; car avialability has a value of 60.22 in BnlL and 31.6 in HEVnlL; personal income has importance values of 34.7 in BnlL and 16.24 in HEVnlL. The dominating influence of age in stratifying VTTS is clear, although much more so for the HEVnlL analysis.

The two trees derived from CARTS are summarised in Figures 5a and 5b, together with the mean VTTS for the sub-sample, the number of observations in each part of the tree, and the socio-economic partitioning variable. The variation in VTTS between socio-economic segment is quite substantial, ranging from $5.89 to $9.97 around a mean of $7.29 for the BnlL model, and, from $6.34 to $10.2 (excluduing one clear outlier of $3.86) around a mean of $7.36 for the HEVnlL model. The combined impact of personal age and personal income in identifying the market segments with different mean VTTS is clear. The further disciminatory role of car availability (defined by the ratio of number of cars to number of workers) is a very strong influence on splitting a mean VTTS by as much as 15%.


VTTS Drive Alone for BnlL and HEVnlL
70
60
50
40
30
20
10
0
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8
8.5
9
9.5
10
10.5
11
VTTS ($/person hour)
Bnll-DA
HEVnlL-DA


VTTS Ride Share BnlL and HEVnlL Models
60
50
40
30
20
10
0
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8
8.5
9
9.5
10
10.5
11
VTTS ($/person hour)
BnlL-RS
HEVnlL-RS





Figures 1 - 4 Distribution of VTTS for BNIL and HEVnlL

Conclusions

This paper offers a number of important insights into the benefits of generalising valuation from point estimates to functions, and the implications that relatively restrictive assumptions on the nature of variation in unobserved yet potentially important influences on choice behaviour might have in the definition of the distribution of values of attributes in a population. The approach has obvious merit in the valuation of the wider set of influences on individual behaviour, especially the growing set of environmental considerations (Daniels 1996).

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Appendix A.

The Contextual Statement Associated with the Travel Choice Experiment

We would now like to ask some questions about your trip TO work. We need to speak to the person in the household who completed the Commuter Questionnaire.

IF THERE IS NO COMMUTER IN THE HOUSEHOLD GO TO QUESTION 14

How long does it take you to travel to work, door to door, on a normal day (ie. without any abnormal traffic or public transport delays) READ OPTIONS

Less than 30 minutes 1
30 to 45 minutes.......................................2
Over 45 minutes 3

SELECT THE RELEVANT SET OF CHOICE CARDS FOR THE RESPONDENT'S TRAVEL TIME

We are going to show you 3 possible choices of transport options in your area. We are not suggesting that these changes will happen in your area, we are just using these options to understand how individuals and households choose to cope with possible changes to transport. We need your help to try to understand how transport facilities can best service your needs under a variety of possible conditions.

We would like you to consider each choice with reference to your current trip TO work.

TRAVEL CHOICE 1.

CHOOSE A SET OF THREE CARDS AT RANDOM FROM THE TRAVEL TIME SET WHICH IS RELEVANT FOR THE RESPONDENT. TAKE ONE OF THOSE CARDS. WHAT IS THE NUMBER OF THE CARD ___________

This is the first choice. (SHOW THE RESPONDENT THE CARD AND EXPLAIN THE FEATURES OF THE OPTIONS)
If these were the options available for your trip to work, which one would you choose?

Car toll route...1
Car no toll route..2
Bus...3
Train..4
Light rail (Tram)..5
Busway 6
(A busway is a dedicated lane for buses which extends for most of your trip)

Which set of times did you consider when you were thinking about getting to/from the public transport options (regardless of whether you chose public transport)?

From home:
Walk.......................................1
Car/bus 2

To your destination:
Walk.............................1
Bus 2

If you were to travel by private vehicle on either a toll or a no toll route (regardless of whether you chose these options), would you

Drive alone 1
Carpool or share a ride as driver 2
Carpool or share a ride as passenger 3

If these were the set of travel choices that were available for your trip to work, do you find them so unattractive that you would seriously consider

	Yes	No
Changing your work place	1	2
Changing where you live	1	2

IF THE RESPONDENT CHOSE EITHER OF THE CAR OPTIONS CONTINUE WITH THE FOLLOWING QUESTION, IF NOT GO TO CHOICE 2.

Given the choice that you have made to travel by private vehicle on a (TOLL/NO TOLL ROUTE) how would this affect the time that you leave home compared with now. Would you leave

Earlier, if so by how many minutes ....1 ________mins
Later, if so by how many minutes ....2 ________mins
At the same time 3

TableA1. Example of the Format of a Travel Choice Experiment Showcard

SA101	1. **CAR TOLL ROAD**		2. **CAR NO TOLL**	
Travel time to work	**10 min.**		**15 min.**	
Time variability	**None**		**None**	
Toll (one way)	**$1.00**		**free**	
Pay toll if you leave at this time (otherwise free)	**6-10 am**		**—**	
Fuel cost (per day)	**$1.00**		**$3.00**	
Parking cost (per day)	**Free**		**Free**	

	3. **BUS**		4. **TRAIN**	
Total time in the vehicle (one way)	**10 min.**		**10 min.**	
Time from home to your closest stop	Walk **5 min.**	Car/Bus **4 min.**	Walk **5 min.**	Car/Bus **4 min.**
Time to your destination from the closest stop	Walk **5 min.**	Bus **4 min.**	Walk **5 min.**	Bus **4 min.**
Frequency of service	**Every 5 min.**		**Every 5 min.**	
Return fare	**$1.00**		**$1.00**	

Appendix B

Description of Variables in the Travel Choice Experiment

Travel Time to Work

There are three different sets of showcards representing short (under 30 minutes), medium (30-45 minutes) and long (45 minutes and over) commutes. They are matched to the commute times currently experienced by respondents. Within each set of showcards, there are three levels of travel times. All public transport options have the same levels as each other, allowing for different combinations across the public transport pairs in each replication. Having the levels the same enables us to investigate the influence that image (through the mode-specific constants) plays in determining preferences within the public transport modes after allowing for the influence of the balanced set of attributes and levels in the design. Travel times on the tolled road have been selected so that it is never worse than the time on the non-tolled route.

Pay Toll if You Leave at this Time (otherwise free)

The tolled route option only has a toll at peak congestion times. The peak over which the toll applies is varied to see what impact a short, medium and long toll period have on mode and departure time decisions.

Toll (one-way)

The toll only applies to the tolled routes when the respondent's commute trip commences within the times specified by the previous variable. There are three levels of toll for each travel time set, with toll levels increasing for the longer travel time sets. Tolls in excess of current tolls in Sydney have been included to assess the impact of increases beyond the current levels in one City. The toll on the M4 in Sydney is $1.50 for a car; the M5 toll is $2 on the section, currently in place, but is likely to increase up to $4 when the second section is open. Tolls in the experiment vary from $1 to $6.

Fuel Cost (per day)

Fuel cost is varied from current levels to a tripling of current levels to assess possible changes commuters will make as a response to large increases in fuel prices. The daily fuel cost for the commute trip on the tolled road is assumed to be equal to or lower than that experienced on the non-tolled route. Fuel costs can be as high as $15 per day for trips in excess of 45 minutes on a free route. This represents a tripling of fuel prices.

Parking Cost (per day)

Another method for reducing the attractiveness of private vehicle use, particularly in central city areas, is to increase parking charges. Three levels of parking charge are used in the experiment to see how sensitive respondents are to parking costs. A fixed set of charges ranging from free to $20 in evaluated.

Travel Time Variability

This variable is calculated for private vehicle modes only, with levels based on 0, ±20% and ±30% of the average trip time on "no toll" roads, and 0, ±5%, and ±10% of the average trip time for "tolled routes". Toll roads will always be equal to or better than non-tolled roads on trip reliability.

Total Time in the Vehicle (one-way)

For public transport only, this variable refers to the time spent travelling on a train, bus, light rail (LRT) or busway. There are three travel time sets to match those of private vehicles. Only two public transport systems are compared or traded off at once to make the experiment more realistic for the respondent. Thus, there are 4 sets of public transport combinations, listed above. Any other combinations are not meaningful. All public transport options share the same experimental levels enabling the investigation of the role of image in respondent's preferences.

Frequency of Service

This variable gives the number of minutes between each service, and has three levels. The frequency for all modes has a range from a low of 5 minutes to a high of 25 minutes. *Time from Home to Your Closest Stop*

The distance from the respondent's home to the public transport stop, in minutes, is measured in both walk time and time travelling by a motorised form of transport. The respondent will be asked to indicate which means of access they would us if they were to use public transport. There are three levels: 5,15 and 25 minutes walk time, and 4,6 and 8 minutes by a motorised mode. This same logic is applied to the *Time to Your Destination from the Closest Stop* except that the only motorised mode available is bus. It is very rare that a commuter will use a car to complete a trip after alighting from public transport. The taxi option is excluded.

Return Fare

This variable gives the return fare in dollars. This has three levels, with the same fare sets being used for all public transport modes for each trip length.