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The Sensitivity of the Valuation of Travel Time Savings to the Specification of Unobserved Effects

By

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ABSTRACT: The behavioural value of travel time savings (VTTS) remains a controversial data item in the evaluation of transport projects. Over the last 40 years we have seen numerous empirical studies seeking to enrich our understanding of the amount that an individual or firm is willing to pay to save a unit of travel time (or more precisely transfer a fixed amount of time from one activity to another). With few exceptions, the majority of empirical studies have used essentially the same data metric and model estimation procedure. The most popular approaches have used either revealed preference (RP) or stated preference (SP) data and a multinomial logit (MNL) choice model to identify marginal rates of substitution between travel time and price of a trip. The few more advanced studies have integrated RP and SP data and have explored the gains in behavioural power of models that relax to varying degrees the underlying assumptions that produce the MNL model. This paper highlights the potential gains from a more carefully considered structure of the unobserved effects conditioning the form of a discrete choice model, and hence the possible mis-inference from the simpler MNL specification. We demonstrate the implication for VTTS of serial correlation between the SP treatments, covariance amongst alternatives, the presence of individual specific (random) effects or heterogeneity, and differential variance of the unobserved effects.

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Introduction

Behavioural values of travel time savings (VTTS) and their associated resource values used in benefit-cost studies are typically obtained from either a simple multinomial logit (MNL) model or a nested logit (NL) model (see Hensher (1978) for a review up to the late 1970's and Wardman (1998) for a more recent review of British evidence). Initially Revealed Preference (RP) data was the only source of data for model estimation, with early suggestions by SCPR, Hensher, and Lee and Dalvi (reviewed in Hensher 1978) that stated preference (SP) data may be useful as a complementary or alternative source of data. This early research on the possible role of SP data focussed on two methods: a transfer price approach (ie an explicit statement on how much an individual is willing to pay to make them indifferent between mixtures of trip time and trip cost); and a budget allocation (or preference priority) task in which a fixed budget is allocated to travel and other activities.

There was an historical sense of unease about these speculative methods since the links with an acceptable theory of the allocation and valuation of time was not offered. There was however a growing concern about the quality of RP data as an appropriate empirical setting within which to observe and measure the trade-off between travel time and cost. The key issues included the errors in measurement of attributes of non-chosen alternatives that were obtained from a respondent (ie reported –perceived levels), the lack of variability and artificiality of network data as an alternative to reported-perceptions, especially if reported data was used to represent the chosen alternative with network data assigned to the non-chosen alternatives; and the general lack of richness of observed time-cost trade-offs in many real markets.

While not denying that the preferences of individuals are what drive individuals travel choices, the opportunity to evaluate a broader and internally richer distribution of time-cost trade-offs was increasingly denied by RP data. This lack of variability is confounded with the high degree of correlation between times and costs, especially where the data is derived from networks and where there is a general absence of intervening effects such as traffic congestion that make both time and cost a strong function of distance. RP data has also tended to limit the range of alternative-specific attributes because of measurement concerns. This is most notable for constructs such as convenience, comfort and reliability.

An alternative data paradigm emerged in the late 1970s (Louviere and Hensher 1983). As a redefinition of the SP approach of earlier years, the focus was not on a different set of measures of trading between time and cost but a respecification of the way in which the choice outcome and the atttribute levels were defined. In contrast to RP data in which the choice outcome was exactly known (by observation) and the attributes of each alternative were measured with error (due the reporting process), SP data were defined by a set of attributes with precise levels and a choice outcome that was reported with error. Although the initial SP models were based on a rating or ranking exercise, which gave them limited credibility within the economic paradigm that drove the theoretical underpinning of the valuation of travel time savings, the turning point of acceptance came when it was shown that SP data with a choice response is identical to RP data except for its measurement and specification properties (Louviere and Hensher 1983, Woodworth and Louviere 1983, Hensher 1994).

Since the mid-80's we have seen an explosion of studies centred on the use of mixtures of RP and SP data to derive empirical measures of VTTS. With an emphasis on valuation, stand-alone SP data is most attractive, since it is rich in preference revelation information. The inclusion of RP data, while important for predicting choice share, demand and deriving elasticities (given the role of the alternative-specific constants in determining choice probabilities), is not important in calculating the marginal rates of substitution between pairs of attributes (see Hensher 1998b for more details). Thus a focus on SP data is in order.

The discussion above suggests that there are many influences to take into account when studying and explaining the preferences and hence choice behaviour of individuals. Some of these influences are measured with great accuracy, some are measured with error and some are excluded. The set of unobserved influences which must be accommodated in the estimation of the choice model might be correlated across the alternatives in the choice set (ie non-zero covariance), and with multiple profiles (or treatments) common in SP studies, the possibility of profile correlation is real (often called serial correlation). Furthermore when all these potential sources of variability in preferences and choice response are taken into account, there may still remain additional sources of influence that are unique to each individual. Allowing for these idiosyncracies of individuals is known as accounting for heterogeneity (via either a random effects or fixed effects specification). We tend to emphasise a random effects specification when the sample size is large otherwise we would need a unique parameter for each individual (minus one), which is not possible without a very large number of treatments for each sampled individual.

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

$$U_{qjt} = a_{qj} + p_{qjt} g_{q} + x_{qjt} b_{q} + e_{qjt} \qquad (1)$$

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

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

$$w_{qjt} = \hat{a}_{q} + p_{qjt}\,\hat{g}_{q} + x_{qjt}\,\hat{b}_{q} + e_{qjt} \qquad (2)$$

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

$$\mathrm{var}(w_{qjt}) = s_a^2 + p_{qjt}^2 \ s_g^2 + x_{qjt}^2 \ s_b^2 + s_e^2 \qquad (3)$$

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

$$\mathrm{cov}(w_{qjt}, w_{qj,t-1}) = s_a^2 + p_{qjt} \, p_{qj,t-1} \ s_g^2 + x_{qjt} \, x_{qj,t-1} s_b^2 \qquad (4)$$

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

Second, equation (4) shows how preference heterogeneity leads to serially correlated errors. That heterogeneity is a special type of serial correlation is not well understood in the transportation literature. To obtain efficient estimates of choice model parameters one should include a specification of the heterogeneity structure in the model. But more importantly, if preference heterogeneity is present it is not merely a statistical nuisance requiring correction. Rather, one must model the heterogeneity in order to obtain accurate choice model predictions, because the presence of heterogeneity will alter cross-price elasticities, marginal rates of substitution between attributes, and lead to IIA violations.

This example suggests the importance of paying attention to the behavioural source of the error terms in a choice model which may lead to new insights into how the model should be estimated, interpreted and applied. We take this perspective in setting out a framework for incorporating the range of error processes represented by the specification of the unobserved effects.

Section 2 lays out a general structure of the choice process, delivering a number of alternative model specifications in terms of the structure of the unobserved effects. This is followed by a discussion of the empirical context in which a set of SP models are estimated. The empirical findings on the valuation of travel time savings are presented in Section 4 together with an interpretation of the policy implications of preserving the simplicity of the MNL (and even NL) model as the dominating source of VTTS.

A Framework for Establishing the Role of Unobserved Effects in Discrete Choice Models

A general framework within which alternative error processes can be specified is presented in this section. We define a choice set of J mutually exclusive alternatives in each SP profile (or treatment) t= 1,…,T. In each choice profile, it is assumed that choices are made according to the well known random utility maximisation hypothesis, where the (indirect) utility of alternative j in profile t is the sum of a deterministic component (defining the observed influences) and a random component.

The generalised utility expression can be written as equation (5).

$$u_{jqt}=X_{jqt}\alpha + y_{qt}\beta_j + \varepsilon_{jqt} \quad (5)$$

where:
u_{jqt} is the latent *utility* of alternative j as perceived by individual q in SP profile t
X_{jqt} are alternative-specific *attributes* of alternative j as perceived by individual q in SP profile t
y_{qt} are individual-specific *characteristics* of individual q in SP profile t
ε_{jqt} is the multinormal error with $\text{cov}(e_q)=\Omega$
where Ω is I×T, permitting inter-alternative and inter-temporal correlation between e_{jqt} and e_{kqs} for the same individual q, and
α, β_j, and Ω are unknown parameters to be estimated.

A number of error covariance structures can be specified as special cases of the general model. We distinguish between two broad classes – specifications subject to the independence of irrelevant alternatives (IIA) condition and those in which it is relaxed. We drop the q subscript for convenience without loosing any information. Within the class of IIA forms, there are four interesting cases:

1. IIA - *case 1*: treating the SP profiles as a pooled cross-section with no inter-profile linkages. This is the classical MNL model under an EVI distribution or a simple probit model under a normal distribution. The D = (J-1)*T dimensional integral of choice probabilities collapses to D one-dimensional integrals.

2. IIA – *case 2*: treating the SP profiles as displaying the property of inter-treatment linkages and introducing a random effects structure by specifying

   $$\varepsilon_{jt} = \alpha_j + \nu_{jt} \text{ with } \nu_{jt} \text{ iid, } j=1,\ldots,J\text{-}1 \quad (6)$$

   as a block-diagonal equi-correlation structure of the covariance matrix with (J-1) standard deviation parameters α_j and ν_{jt} standard deviations normalised to 1.0. These parameters can be identified when we have multiple observations across each sampled individual as is the case with an SP profile. α_j represents the individual-specific (or idiosyncratic) effects commonly referred to as unobserved homogeneity within an individual such as attitudes and opinions. If not accounted for it may lead to spurious correlation amongst the alternative-specific unobserved effects across SP profiles. In a single cross-section, the exposure of heterogeneity is dependent on variation across a sample of individuals.

3. IIA – *case 3*: treating the SP profiles as displaying the property of inter-treatment linkages and introducing an autoregressive error structure of the form

   $$\varepsilon_{jt} = \rho_j\, \varepsilon_{jt-1} + \nu_{jt} \text{ with } \nu_{jt} \text{ iid, } j=1,\ldots,J\text{-}1 \quad (7)$$

   This is a block-diagonal structure of the covariance matrix where each block is an AR(1) process. J-1 (ρ_j) parameters have to be estimated. SP modellers are turning their attention to this potential source of bias in parameter estimates, commonly referred to in transportation as serial correlation (eg Morikawa 1994, Kim 1998).

4. IIA – *case 4*: treating the SP profiles as displaying the property of inter-treatment linkages and introducing both random effects and an autoregressive error structure of the form

   $$\varepsilon_{jt} = \alpha_j + \eta_{jt}, \ \eta_{jt} = \rho_j \eta_{jt-1} + \nu_{jt} \text{ with } \nu_{jt} \text{ iid, } j=1,\ldots,J-1 \tag{8}$$

   Equation (8) overlays the equi-correlation structure of the covariance matrix with the AR(1) structure. Provided ρ_j <1, the two unobserved effects are separately identified.

Within the class of non-IIA forms, there are also four interesting cases, each structured according to different assumptions on the inter-temporal error specification:

5. Non-IIA – *case 5*: imposing the condition of no inter-temporal correlation between ε_{jt} across SP profiles but the presence of correlation across the alternatives in a choice set that are constant over the SP profiles. This is the classic cross-sectional multinomial probit model with a structured covariance matrix. We have a simple block-diagonal structure for the covariance matrix with T*(J-1) – dimensional blocks. There are J-2 variances and (J-1)*(J-2)/2 covariances that can be identified.

6. Non-IIA – *case 6*: The random effects specification overlays case 5, nullifying the block-diagonal structure. (J-1) variances of the random effects can be identified in addition to the inter-alternative correlations in case 5. The random effects can also be correlated for each pair of alternatives across all SP profiles.

7. Non-IIA – *case 7*: The autoregressive error structure can be overlayed on the base case 5 structure of the form

   $$\varepsilon_{jt} = \rho_j \varepsilon_{jt-1} + \nu_{jt} \text{ with corr } (\nu_{jt}, v_{js}) \quad 0 \text{ if } \ t=s \text{ and 0 otherwise} \tag{9}$$

   That is, the ν_{jt} are corelated across alternatives but uncorrelated across SP profiles. J-1 additional parameters (ρ_j) in the covariance matrix have to be estimated.

8. Non-IIA – *case 8*: The final model allows for inter-alternative correlation, random effects and autoregressive errors, producing the most general error structure considered herein:

   $$\varepsilon_{jt} = \alpha_j + \eta_{jt}, \ \eta_{jt} = \rho_j \eta_{jt-1} + \nu_{jt}, \ j=1,\ldots,J-1 \tag{10}$$

   with corr (ν_{jt}, v_{is}) 0 if t=s and 0 otherwise and cov (α_i, α_j) = σ_{ij}.

   The global covariance (for 10) is

   $$\text{Cov}(\varepsilon_{it}, \varepsilon_{jt}) = \sigma_{ij} + \rho_j^{(t-s)} \frac{\sqrt{(1-r_i^2)}\sqrt{(1-r_j^2)}}{1-r^i r^j} w_{ij} \tag{11}$$

Where ω_{ij} = corr (ν_{jt} , v_{is}) if SP profile t = SP profile s.

Estimation of the full set of specifications ranges from a simple IIA/iid probit model to a complex multi-period non-IIA/non-iid multinomial probit model. The cumulative distribution function herein is assumed to be multivariate normal and characterised by the covariance matrix *M*. Estimating the parameters is a complex task when we move beyond the simple MNL and NL models. In the most general case we need to evaluate an E = (I-1)*T dimensional integral for each individual and each iteration in the maximisation of the (log) likelihood function. What makes this particularly complex is the inter-alternative correlation on one or more of the error components. Numerical integration is not computionally feasible since the number of operations increases with the power of E, which dimensions the covariance matrix. Simulation of the choice probabilities is the preferred method of estimating all parameters, by drawing pseudo-random realisations from the underlying error process (Boersch-Supan and Hajivassiliou 1990).[1]

The popular method is one initially introduced by Geweke (and improved by Keane, McFadden, Boersch-Supan and Hajivassiliou - see Geweke et al 1994, McFadden and Ruud 1994) of computing random variates from a multivariate truncated normal distribution. Although it fails to deliver unbiased multivariate truncated normal variates (as initially suggested by Ruud and detailed by Boersch-Supan and Hajivassiliou (1990)), it does produce unbiased estimates of the choice probabilities. The approach is quick and generated draws and simulated probabilities depend continuously on the parameters β and M. This latter dependence enables one to use conventional numerical methods such as quadratic hillclimbing to solve the first order conditions for maximising the simulated likelihood function (equation 12); hence the term simulated maximum likelihood (SML) (Stern 1997).

$$\bar{L}(b, M) = \prod_{r=1}^{R} \prod_{q=1}^{Q} \bar{P}_r(\{i_q\}) \tag{12}$$

Boersch-Supan and Hajivassiliou (1990) have shown that the choice probabilities are well approximated by the formula (13), even for a small number of replications. Our experience suggests that 100 (=R) replications is sufficient for a typical problem involving five alternatives, 1000 observations and up to 10 attributes.

$$\bar{P}(\{i_q\}) = \frac{1}{R}\sum_{r=1}^{R} \bar{P}_r(\{i_{qr}\}) \tag{13}$$

The Data Source

The data is drawn from a larger 1997 study investigating the potential demand for high speed rail in the non-business market for the Sydney-Canberra corridor currently served

[1] Bhat (1999) however has shown that an alternative quasi-random maximum simulated likelihood method which uses non-random more uniformly distributed sequences instead of pseudo-random points provides greatly improved accuracy with far fewer draws and computational time.

by car, a road distance of 270 kilometres from the outskirts of Sydney to central Canberra.

Using a stated choice switching paradigm, each sampled car traveller was asked to review four alternative high speed rail options defined by fare class (first, full economy, discount economy and off-peak), frequency (every 30 minutes, hourly and two hourly), and parking cost ($2 - $20 per day); and asked to select one of them or stay with the car for the current trip. All 355 individuals completed up to two profiles and 81 completed up to four profiles. A total sample of 870 observations were used in model estimation.

Design of stated preference experiment

The SP experiment is based on a single fractional factorial design, with the actual levels of attributes varying depending on whether a trip is long, medium or short. Trip lengths are respectively 70-100 minutes, 40-60 minutes and 10-30 minutes. The station pairs for each trip length are Parramatta/Sydney/Airport to Canberra (long trips), Campbelltown to Canberra or Goulburn to Sydney (medium trips), and Goulburn to Canberra or Bowral to Sydney (short trips). The attributes levels are summarised in Table 1.

Table 1. Attribute levels for each trip length

Attribute	**Long**	**Medium**	**Short**
Linehaul time (mins)	60, 80, 100	40, 50, 60	10,20,30
Fares - first class ($)	115, 95, 75	115, 95, 75	115, 95, 75
Fares - Full economy ($)	70, 60, 50,	70, 60, 50,	70, 60, 50,
Fares - Disc economy ($)	45, 35, 25	45, 35, 25	45, 35, 25
Fares - off-peak ($)	40, 30, 20	40, 30, 20	40, 30, 20
Fares - family disc ($)	50%, 30%, 10%	50%, 30%, 10%	50%, 30%, 10%
Parking price ($) *	10/15/20; 2/4/6	10/15/20; 2/4/6	10/15/20; 2/4/6
Frequency (‘every..hrs)	1h, 2h, 3h	1h, 2h, 3h	1h, 2h, 3h

*Note: * the first set of parking prices apply to Sydney Central, the rest to all other stations. All fares are one-way adult fares*

The range of fares has been selected to accommodate an application with very low fares for short trips (ie $20 off peak and $10 per head if a family discount) and low fares for long trips of $40 or $20 if a family discount. The high end captures $115 per one-way trip. Travel times have been selected to establish sufficient variability within each of the trip segments. In informing a respondent about parking facilities, it is assumed that all parking is secure and available at the offered price.
The 3^8 full factorial design has been reduced to the fraction summarised in Table 2. There are 27 profiles with six residual degrees of freedom. The design is perfectly orthogonal. Because all attributes are numerical, and their preference directionality is known a priori, there is the possibility of dominant or dominated profiles. We used a 3^{7-4} orthogonal fraction to create the 27 profiles (Louviere et al 1999).

Table 2. Attribute Profiles for High Speed Rail
Notes: 0 = low level, 1 = medium level, and 2 = high level for each attribute. Each column is an attribute, each row is a mix of attribute levels for the 8 attributes. Each row must have an identifier.

Row number	**8 attributes by level**	**Row number**	**8 attributes by level**
1	0 0 0 0 0 0 0 0	15	1 1 2 0 1 0 2 1
2	0 0 1 1 1 2 1 2	16	1 2 0 1 0 0 2 2
3	0 0 2 2 2 1 2 1	17	1 2 1 2 1 2 0 1
4	0 1 0 0 1 1 2 2	18	1 2 2 0 2 1 1 0
5	0 1 1 1 2 0 0 1	19	2 0 0 2 2 2 2 2
6	0 1 2 2 0 2 1 0	20	2 0 1 0 0 1 0 1
7	0 2 0 0 2 2 1 1	21	2 0 2 1 1 0 1 0
8	0 2 1 1 0 1 2 0	22	2 1 0 2 0 0 1 1
9	0 2 2 2 1 0 0 2	23	2 1 1 0 1 2 2 0
10	1 0 0 1 1 1 1 1	24	2 1 2 1 2 1 0 2
11	1 0 1 2 2 0 2 0	25	2 2 0 2 1 1 0 0
12	1 0 2 0 0 2 0 2	26	2 2 1 0 2 0 1 2
13	1 1 0 1 2 2 0 0	27	2 2 2 1 0 2 2 1
14	1 1 1 2 0 1 1 2		

The Evidence

All models except the basic multinomial logit (MNL) model were estimated using pseudo-random SML with 100 replications in the simulation estimator. All of the models are described by a likelihood function which is a product of the choice probabilities (equation 14) across the sample of q=1,...,Q individuals, i=1,...,I alternatives and t=1,....T SP profiles.

$$L(b,M) = \prod_{q=1}^{Q} P(\{i_{tq}\} \mid \{X_{itq}\}; b, M \qquad (14)$$

All models have been estimated with alternative-specific constants for car and three high speed rail fare class alternatives, generic in-vehicle time, generic access plus egress time and generic line-haul cost. All parameter estimates used in the derivation of mean VTTS are statistically significant at the 95% level or better unless otherwise indicated.

The set of models representing IIA cases 1-4 are summarised in Table 3 and those for the non-IIA Cases 5-8 are summarised in Table 4. In addition we present a variant of the correlated alternatives MNP in which only the variances of the unobserved effects are unrestricted (which we call heteroskedastic multinomial probit (H-MNP)). This model is similar to the heteroskedastic extreme value (HEV) model (Bhat 1995, Hensher 1997, 1998a) but under a multinormal distribution instead of an extreme value distribution. It is reported in Table 3 even though it relaxes the identically distributed condition while maintaining the independence assumption.

Table 3 Summary of Model Estimation Results for IIA Models

Attributes	Case 1 (MNL)	Case 2	Case 3	Case 4	H-MNP
Car ASC	0.19 (0.5)	-1.09 (-1.2)	.203 (.72)	-.526 (-.64)	-1.49 (-1.6)
First class ASC	1.96 (6.4)	-3.51 (-2.0)	1.21 (6.3)	.056 (.08)	-11.58 (-1.2)
Full Y ASC	1.13 (6.1)	1.11 (2.5)	.791 (6.5)	1.844 (6.8)	2.09 (6.1)
Disc Y ASC	0.84 (6.0)	0.83 (5.6)	.585 (5.9)	.480 (2.7)	.520 (3.9)
In vehicle time	-.0039 (-2.4)	-.014 (-2.3)	-.003(-1.7) *	-.0133 (-4.1)	-.013 (-2.0)
Out of vehicle time	-.0135 (-3.6)	-.036 (-4.1)	-.011 (-4.4)	-.029 (-4.0)	-.042 (-2.5)
Line haul cost	-.0498 (-8.5)	-.119 (-9.2)	-.031 (-8.9)	-.108 (-10.5)	-.102 (-3.9)
Random Effects α_i:					
RE – std car		4.37 (8.6)		3.70 (7.9)	
RE – std first class		8.40 (5.1)		5.57 (7.4)	
RE – std Full Y		2.76 (6.3)		1.58 (6.4)	
RE – std Disc Y		0.01 (1.6)		2.03 (5.4)	
RE – std off peak		0.0 (fixed)		0.0 (fixed)	
RE – corr car,fc					
RE – corr car,fy					
RE – corr car, dy					
RE – corr car, op					
RE – corr fc, fy					
RE – corr fc, dy					
RE – corr fc, op					
RE– corr fy,dy					
RE – corr fy,op					
RE – corr dy,op					
Unobserved Utilities:					
MNP – std car	1.0 (fixed)	1.0 (fixed)	1.0 (fixed)		4.510 (4.4)
MNP – std first class	1.0 (fixed)	1.0 (fixed)	1.0 (fixed)		12.70 (4.7)
MNP – std Full Y	1.0 (fixed)	1.0 (fixed)	1.0 (fixed)		.584 (-.8)
MNP – std Disc Y	1.0 (fixed)	1.0 (fixed)	1.0 (fixed)		1.12 (.33)
MNP – std off peak	1.0 (fixed)	1.0 (fixed)	1.0 (fixed)		1.0 (fixed)
MNP – corr car,fc					
MNP – corr car,fy					
MNP – corr car, dy					
MNP – corr car, op					
MNP – corr fc, fy					
MNP– corr fc, dy					
MNP – corr fc, op					
MNP– corr fy,dy					
MNP – corr fy,op					
MNP – corr dy,op					
Autocorrelations ρ_i:					
AR1 – car			.982 (3.4)	-.05 (-.2)	
AR1 – first class			.926 (5.8)	.906 (10.2)	
AR1 – full Y			.937 (5.9)	.978 (39.2)	
AR1 – disc Y			.863 (7.5)	0.798 (-6.2)	
AR1 – off peak			0.0 (fixed)	0.0 (fixed)	
vtts	4.63 (5.37 #)	6.88	4.98 *	7.35	7.64
Log-likelihood	-1067.9	-779.9	-811.5	-771.9	-1040.2

* not statistically significant due to a non-significant parameter for in-vehicle travel time.
#= value of time savings for an mnp model equuivalent to an mnl model except that latter is a cumulative normal in contrast to extreme value type I.

Table 4 Summary of Model Estimation Results for non-IIA Models

Attributes	Case 5 (MNP)	Case 6	Case 7	Case 8
Car ASC	-1.527(-1.63)	-2.32 (-1.6)	-1.211 (-1.5)	-1.724 (-2.1)
First class ASC	-9.169 (-1.35)	-9.993 (-1.9)	-.815 (-1.0)	-4.799 (-4.0)
Full Y ASC	2.149 (9.35)	1.936 (2.9)	1.44 (5.2)	1.871 (2.3)
Disc Y ASC	0.554 (5.2)	0.231 (0.6)	.526 (3.8)	0.755 (3.6)
In vehicle time	-.0147 (-2.2)	-.0198 (-1.98)	-.01589 (-4.6)	-.02207 (-5.9)
Out of vehicle time	-.0454 (-2.8)	-.0558 (-3.3)	-.0408 (-6.7)	-.0656 (-7.9)
Line haul cost	-.1089 (-8.6)	-.1645 (-6.4)	-.0978 (-9.2)	-.1414 (-6.8)
Random Effects α_i*:*				
RE – std car		6.490 (4.0)		6.953 (4.8)
RE – std first class		14.38 (3.9)		10.633 (6.9)
RE – std Full Y		3.466 (5.4)		3.256 (4.1)
RE – std Disc Y		1.733 (4.2)		1.0 (fixed)
RE – std off peak		0.0 (fixed)		0.0 (fixed)
RE – corr car,fc				
corr car,fy				
RE – corr car, dy				
RE – corr car, op		.5494 (1.41)		
RE – corr fc, fy		.7716 (5.8)		.7507 (4.8)
RE – corr fc, dy				
RE – corr fc, op				
RE– corr fy,dy				
RE – corr fy,op				
RE – corr dy,op				
Unobserved Utilities:				
MNP – std car	4.933 (3.7)	1.586 (3.5)	4.609 (6.5)	2.346 (3.1)
MNP – std first class	11.57 (2.5)	4.095 (3.4)	5.737 (7.7)	2.113 (3.7)
MNP – std Full Y	1.0 (fixed)	1.0 (fixed)	1.987 (5.8)	0.811 (1.7)
MNP – std Disc Y	1.0 (fixed)	1.0 (fixed)	1.045 (4.8)	0.555 (4.5)
MNP – std off peak	1.0 (fixed)	1.0 (fixed)	1.0 (fixed)	1.0 (fixed)
MNP – corr car,fc				
MNP – corr car,fy				
MNP – corr car, dy				
MNP – corr car, op				
MNP – corr fc, fy	.633 (2.0)	.7715 (3.5)	.6540 (5.2)	.867 (4.6)
MNP– corr fc, dy				
MNP – corr fc, op				
MNP– corr fy,dy				
MNP – corr fy,op				
MNP – corr dy,op				
Autrocorrelations ρ_i*:*				
AR1 – car			.949 (104)	.322 (1.3)
AR1 – first class			.958 (56)	-.991 (-43.0)
AR1 – full Y			.827 (9.9)	-.967 (-9.6)
AR1 – disc Y			.996 (270)	0.0 (fixed)
AR1 – off peak			0.0 (fixed)	0.0 (fixed)
vtts	8.09	7.23	9.75	9.33
Log-likelihood	-1039.9	-757.6	-774.2	-753.2

Taking the MNL model as the base (log-likelihood of –1067.9), we see that relaxing the assumption of the structure of the unobserved effects improves the overall statistical performance of all models. The improvement is most notable when unobserved heterogeneity is accommodated (-779.9), especially the standard deviations of the random effects (Case 2 and by implication Case 4). Serial correlation is also a statistically significant influence, both in the presence and absence of unobserved heterogeneity (Cases 3 and 4), reducing the log-likelihood from –1067.9 for MNL to –811.5 and 771.9 respectively. However, in the presence of the standard deviations of the random effects, the combined influence, while a statistical improvement (to –771.9), we find that the serial correlation associated with the car alternative is statistically insignificant (t-value of -.2 in Case 4 compared to 3.4 in Case 3). This is an important finding, suggesting that specific alternatives (in this study it is the base mode), produce spurious correlation as a consequence of ignoring unobserved heterogeneity (the point made above in Section 1 after equation 4).

Relaxing the constant variance assumption (H-MNP) improves on the MNL model (from –1067.9 to 1040.2), but to a far lesser extent than the models that allow for random effects and serial correlation. Interestingly however the mean value of travel time savings for H-MNP is much closer to that for Cases 2-4 than for MNL.

A comparison of the IIA and non-IIA models against the MNL model indicates an important contribution to the overall statistical fit from a less restrictive specification of the unobserved effects. A trace of the log-likelihood values in Tables 3 and 4 suggests that allowing for unobserved heterogeneity through random effects (Cases 2) has the greatest single impact on improving the log-likelihood. However, the pairwise mixing of random effects with serial correlation (Case 4), random effects with correlated alternatives (Case 6), and serial correlation with correlated alternatives (Case 7) all have a significant impact on improving the overall goodness-of-fit.

The behavioural values of non-business travel time savings together with the log-likelihood at convergence are summarised in Table 5, sorted in ascending order. The variation in the VTTS is substantial, ranging from a low of $4.63/adult person hour for the most restrictive model, up to $9.75/adult person hour for a less restrictive specification[2]. This is a sizeable increase in the VTTS. This has major implications for transport investments, given the important role played by time benefits in transport project appraisal. Close inspection of Table 5 suggests that all of the sources of relaxation of the specification of the unobserved effects are contributing influences to the higher mean estimates of VTTS in contrast to the downward biased MNL mean estimate.

Figure 1 provides a graphical summary of the profile of sources of variation in VTTS. The paths leading to the least restrictive model (Case 8) tell a story about the contribution of each source of input into the behavioural representation of the error processes. The trace of random effects is 4.63⇒6.88⇒7.35⇒7.23⇒9.33; for serial correlation it is 4.63⇒4.98⇒7.35⇒9.75⇒9.33; and for correlated alternatives (including unrestricted variance) it is 4.63⇒8.09⇒7.23⇒9.75⇒9.33. From these traces, it is appears that the step up to a higher plane for VTTS occurs almost

[2] The equivalent of the MNL value for probit is $5.36 per person hour. Although greater than the MNL estimate, it is still significantly smaller than for the less restrictive models (excluding case 3 where we had a statistically insignificant parameter for in-vehicle time.

immediately that we relax any restriction, but most notable when we allow for correlated alternatives.

Table 5 Alternative Error Processes in Discrete Choice Models and Implications on Estimate of VTTS (in ascending order)

Model	Case	Error Processes	VTTS	LogL
MNL	1	iid across periods, iid across alternatives	**4.63**	-1067.9
MNP	1a	iid across periods, iid across alternatives	**5.37**	-1075.0
	3	AR1 errors, iid across alternatives	**4.98 ***	-811.5
	2	random effects, iid across alternatives	**6.88**	-779.9
	6	random effects, correlated across alternatives	**7.23**	-757.6
	4	random effects + AR1 errors, iid across alternatives	**7.35**	-771.9
H-MNP		unrestricted variance and iid across periods	**7.64**	-1040.25
	5	iid across periods, free variance, correlated across alternatives	**8.09**	-1039.9
	8	unrestricted variance, correlated across alternatives, random effects, AR1 errors,	**9.33**	-753.2
	7	AR1 errors, correlated across alternatives	**9.75**	-774.2

VTTS is in dollars per adult person hour. AR1 = autoregressive structure, H-MNP = heteroskedastic multinomial probit (correlated alternatives). * = vtts derived from a non- statistically significant parameter for in-vehicle time.

A comparison of evidence from other studies in which a reduced set of alternative error specifications were evaluated confirms the tendency toward higher mean estimates as we relax the restrictions. For example, Bhat (1995) found a VTTS for an MNL model of $Cnd14.68 per person hour for intercity travel in the Toronto-Montreal corridor in contrast to $Cnd20.75 per person hour for an heteroskedastic extreme value (HEV) model. Hensher (1997) found higher mean values for an HEV specification for high speed rail in the Sydney-Canberra corridor, confirmed by Hensher (1999) for the Sydney-Melbourne corridor (MNL: $6.66 per person hour, HEV: $8.19 per person hour).

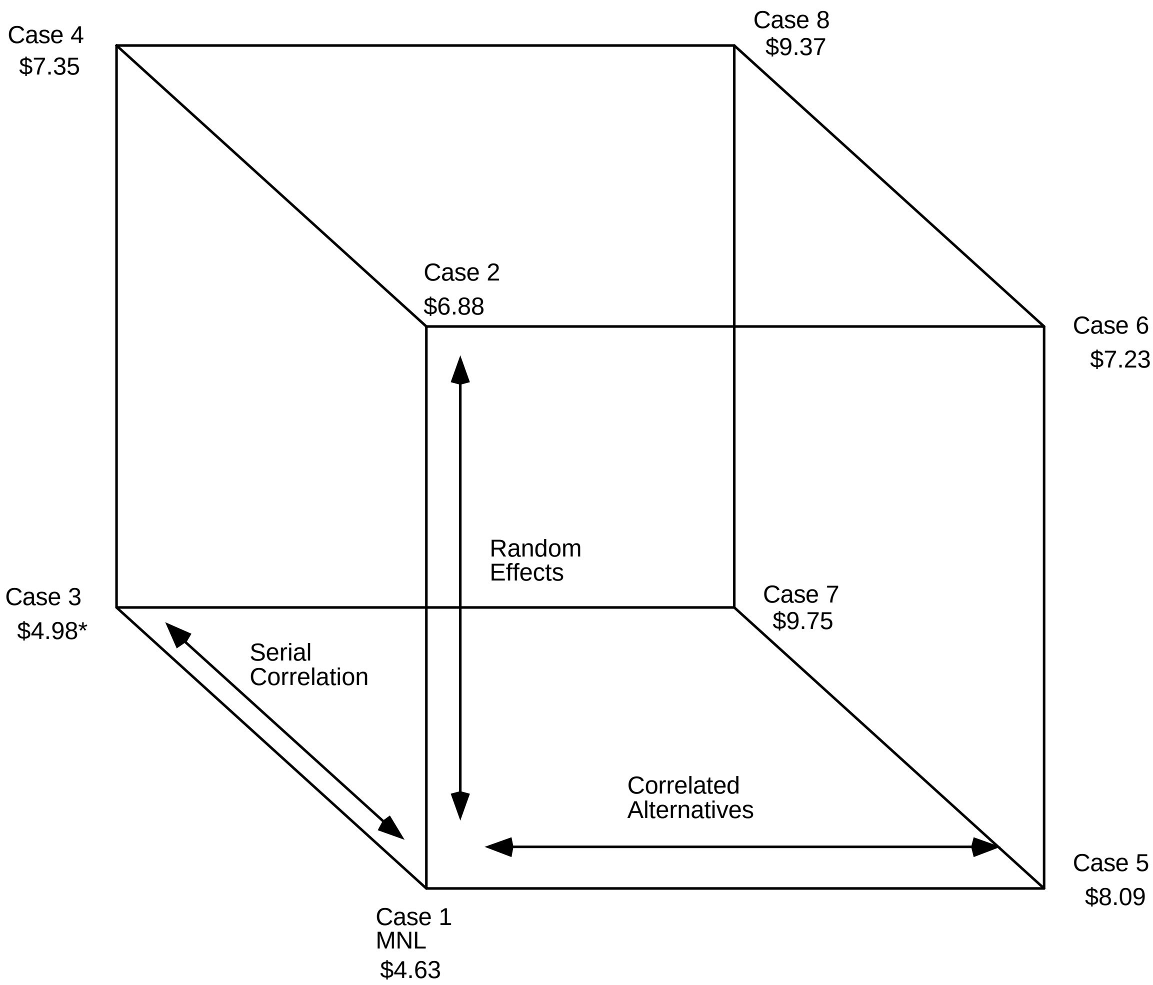

Figure 1. Diagrammatic Representation of Sources of Variation in VTTS

Conclusions

The empirical evidence presented in this paper is a timely reminder of the sensitivity of mean estimates of VTTS to the underlying error structure of a choice model. Since the error structure represents the behavioural role of the range of unobserved influences on the choice behaviour which produces VTTS as its by-product, the importance of establishing the behavioural implications of simplified models such as the IIA/iid model, is critical to the selection of appropriate empirical values of travel time savings for project appraisal.

The evidence presented should be of concern to planners and policy makers, since it suggests that we have tended to *undervalue* travel time savings as a consequence of the way most empirical studies have specified (ie simplified) the behavioural structure of unobserved effects. However, since our new evidence is limited to a single (non-business intercity) data set, we must express caution while at the same time motivating other researchers to explore the implications in other empirical contexts of error structures on VTTS.

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