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A Comparison of Elasticities Derived from Multinomial Logit, Nested Logit and Heteroscedastic Extreme Value SP-RP Discrete Choice Models

by

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ABSTRACT: Developments in the estimation of discrete choice models which relax elements of the independence of irrelevant alternatives (IIA) property of the multinomial logit model (MNL) provide opportunities to explore the richer behavioural sensitivity of a choice model to changes in the levels of attributes influencing choice. Surprisingly, the literature offers limited evidence on the variations in sensitivity (ie elasticity) as we move from an MNL model based on revealed preference (RP) data, to MNL based on stated preference (SP) data, to combined RP-SP data estimated sequentially and jointly with partial relaxation of the differential variance in the unobserved effects by the 'nested logit' method, and then as free variance across all RP and SP alternatives by heteroscedastic extreme value (HEV) estimation. This paper draws on a data set collected in 6 Australian capital cities in 1994 to estimate a series of commuter mode choice models in the presence and absence of two 'new' alternatives (light rail and busway systems), to derive matrices of direct and cross point elasticities for travel cost and travel time. The evidence suggests that constraining the variance of the unobserved effects to varying degrees tends to over-estimate the elasticities sufficiently to distort the real behavioural sensitivity of specific attributes influencing choice. Furthermore, we seriously question the usefulness of studies which rely solely on SP data.

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Introduction

Much progress has been made in understanding individual travel behaviour in the context of a set of modelling paradigms of an essentially economic nature, as represented by the rule of utility maximisation. In the main the application of such modelling paradigms to revealed preference (RP) data in a discrete choice framework has been emphasised in empirical work. Increasingly, however, there has been interest in extending RP data paradigms to incorporate stated choice (SC) data to enrich model estimation in applications in which attribute levels and choice sets extend beyond utility spaces observed in real markets (eg, Hensher's 1994 Special Issue of *Transportation* on SP methods, Bradley and Daly 1992, 1997, Hensher and Bradley 1993, Morikawa 1989, Swait et al 1994, Hensher (in press, forthcoming)).

Growing recognition of benefits potentially gained from fusing complementary sources of preference and choice data has coincided with discrete choice modelling developments which allow relaxation of some of the strong assumptions of the basic multinomial logit (MNL) model. In particular, differences in variance structures associated with unobserved random effects are important features of complementary data sets. MNL models impose constant variance, which translates into a constant (usually "1.0") scale parameter associated with each observed attribute. If scale parameters are not equal to unity, one must take this into account or risk confounding attribute taste weights with scale. Thus, to maintain the MNL form, one must rescale each data set to insure comparability of taste weights, which in turn, permits transferability of information between data sets. A number of rescaling procedures have been developed to implement these ideas, and more general procedures are now available to derive unique scale parameters for each alternative within and between data sets. The purpose of this paper is to undertake a comparison and assessment of the empirical implications of three particular approaches for estimating direct and cross price and travel time choice elasticities: 1) Sequential MNL 2) FIML 'Nested Logit' and 3) Joint Heteroscedastic Extreme Value.

This paper is organised as follows. We begin with an overview of the rationale for rescaling, followed by an outline of the approaches taken to estimate scale parameters and modify models to obtain appropriate estimates of elasticities. Next, the empirical context and study example is discussed, and emphasis placed on a designed choice experiment. Then empirical results are presented which bear on comparisons of estimates of elasticities and values of time savings. The paper concludes with a summary of our major findings.

Relaxing The Constant Variance Assumption

Each attribute in the indirect utility expression associated with an alternative has a beta (β) parameter to reflect 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 is an index of variability in the unobserved effects which can be set equal to one arbitrarily. The simple MNL form assumes that this constant scalar is independent of the alternatives in a choice set; hence it does not affect comparisons of values *across* alternatives (McFadden 1981). Assuming uniqueness may be unsatisfactory. For example, if public transport alternatives exhibit significant unobserved effects with higher variance compared with automobile alternatives, the constant variance assumption can overestimate the value of travel time savings for public transport use relative to automobile use.

To relax the constant variance assumption requires more complex choice models, such as the heteroscedastic extreme value (HEV) model. Allenby and Glinter (1995), Bhat (1995) and Hensher (1997, in press, forthcoming) provide recent examples of HEV model applications. The behavioural choice rule for the HEV model can be characterised as follows:

$P_i = \text{Prob}[U_i > U_j]$ for all j not equal to i (1)

$$= \int_{-\infty}^{+\infty} \pi(j \neq i)\ F(\lambda_j)\{V_i - V_j + \varepsilon_i\}]\lambda_i f[\lambda_i \varepsilon_i] d\varepsilon_i \qquad (2)$$

where f(t) is the density function defined as exp(-t)*exp(-exp(-t)), equal to -F(t)*log(F(t)). The probabilities must be evaluated numerically because there is no closed-form solution for the integral in equation (2). The scale parameter is $\frac{1}{\lambda}$, where λ^2 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); hence, equation (2) can be replaced with equation (3), where w is the weight and z(l) is the abscissa of the Gauss-Laguerre polynomial. A 68 point approximation has proven sufficient in numerical simulations (Greene 1996).

$$\int_{-\infty}^{+\infty} \pi(j \neq i)\ F[t(j|i)]\ \exp[-u(i)]\ du(i) \approx \Sigma(l)\ w(l)\ F(z(l)) \qquad (3)$$

The HEV model is sufficiently flexible to allow differential cross-elasticities among all pairs of alternatives. That is, two alternatives have the same elasticity only if the scale parameter associated with the unobserved components of the indirect utility expressions for both alternatives are equal. The effect of a marginal change in the indirect utility of an alternative *m* on the probability of choosing alternative i may be written as equation (4) - see also Bhat (1995) and Hensher (in press):

$$\frac{\partial P_i}{\partial V_m} = \int_{z=-\infty}^{z=+\infty} -\frac{1}{\lambda_m} \exp\left[\frac{-V_i + V_m - \lambda_i z}{\lambda_m}\right] \prod_{j \in C, j \neq i} F\left[\frac{V_i - V_j + \lambda_i z}{\lambda_j}\right] f(z) dz \qquad (4)$$

where $z = \varepsilon_i/\lambda_i$. The impact of a marginal change in the indirect utility of alternative *i* on the probability of choosing *i* is given in equation (5)

$$\frac{\partial P_i}{\partial V_i} = - \sum_{l \in C, l \neq i} \frac{\partial P_i}{\partial V_l} \qquad (5)$$

The cross-elasticity for alternative *i* with respect to a change in the *k*th variable in the *m*th alternative's observed utility, x_{km}, is

$$\eta^{P_i}_{x_{km}} = \left[\frac{\partial P_i}{\partial V_m} / P_i \right] * \beta_k * x_{km}, \qquad (6)$$

where β_k is the estimated taste weight on the *k*th variable.

The corresponding direct-elasticity for alternative *i* with respect to a change in x_{ki} is

$$\eta^{P_i}_{x_{ki}} = \left[\frac{\partial P_i}{\partial V_i} / P_i \right] * \beta_k * x_{ki}. \qquad (7)$$

Beginning with Bradley and Daly (1992), several authors used nested logit to estimate the values of the scale parameter(s) empirically, thereby allowing RP and SP data sources to be pooled. As well, the 'Nested Logit' (NL) form permits exploration of alternative mixes of scale parameters within and between SP and RP data sources. In such applications, NL simply is a convenient way to organise data to estimate the desired scale parameters as inclusive value parameters, in which case empirical estimates of lambda will be unbounded. Inclusive value(s) parameter(s) allow differences in cross-substitution elasticities in contrast to the IIA restriction resulting from the IID error assumption of MNL. The elasticity formulae for nested logit models depend on whether an alternative (direct elasticity) or a pair of alternatives (cross elasticity) are associated with the same branch in a nested partition. Direct elasticities are identical to the MNL formula for any alternative *m* which is *not* in a partitioned branch (ie, in a non-nested partition of the tree). If alternative *m* is in a partitioned part of the tree, the formula is modified to accommodate correlation between alternatives *within* a branch. The NL direct elasticity for a partitioned alternative is:

$$[(1 - P_m) + \{1/\lambda_G\}(1-P_{m|G})]\beta_k X_{mk} \qquad (8)$$

The NL cross elasticity for alternatives m and m' in a partition of the nest is:

$$-[Pm + \{(1-\lambda_G)/ \lambda_G \}P_{m|G}]\ \beta_k X_{mk} \qquad (9)$$

If statistical tests establish that the λ`s for each branch differ statistically from 1.0, it does not necessarily mean that a tree structure is best in a statistical and/or behavioural sense. Instead, analysts should evaluate several trees, and if the λ`s differ from 1.0, compare the log-likelihood of each tree at convergence using a likelihood ratio test. That tree which exhibits the lowest log-likelihood at convergence <u>and</u> statistically improves the fit is the preferred model.

In general, there are 2^M possible combinations of elemental alternatives without a structured partitioning process. Thus, a priori critieria are required to partition alternatives initially; and the key criterion is anticipated correlations between the random components among elements of each subset. HEV models provide an intuitively appealing way to identify promising tree structure(s), thereby avoiding laborious examination of many potential tree structures.

Specification Of An Empirical Inquiry

A stated choice experiment was part of a broader research effort examining potential impacts 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; Louviere et. al 1994). The universal choice set comprised the currently available modes plus the two 'new' modes of light rail and busway. Respondents evaluated scenarios describing ways to commute between their current residence and workplace locations using different combinations of policy-sensitive attributes and levels. The purpose of the exercise was to observe and model their observed coping strategies in each scenario.

Four alternatives appeared in each travel choice scenario: a) car (no toll), b) car (toll), c) bus or busway, and d) train or light rail. Twelve types of showcards described scenarios involving combinations of trip length (3) and public transport pairs (4): bus vs. light rail, bus vs. train (heavy rail), busway vs. light rail, and busway vs. train. Appearance of public transport pairs in each card shown to respondents was based on an experimental design. Attribute levels are summarised in Table 1 and an illustrative show card is displayed in Table 2. The accompanying contextual questions are reproduced in Appendix A.

Five three-level attributes were used to describe public transport alternatives (each attribute is defined in Appendix B): a) total in-vehicle time, b) frequency of service, c) closest stop to home, d) closest stop to destination, and e) fare. The attributes of the car alternatives were: a) travel times, b) fuel costs, c) parking costs, d) travel time variability, and for toll roads e) departure times and f) toll charges. The design allows orthogonal estimation of alternative-specific main effect models for each mode option: a) car no toll, b) car toll road, c) bus, d) busway, e) train, and f) light rail. Alternative-specific, linear x linear 2-way interaction effects also can be estimated for both car mode, and as generic effects in the case of bus/busway and train/light rail mode.

The master design for the travel choice task was a 27 x 3^{27} orthogonal fractional factorial, which produced 81 scenarios or choice sets. The 27 level factor was used to block the design into 27 versions of three choice sets containing two alternatives. Versions were balanced such that each respondent saw every level of each attribute exactly once. The 3^{27} portion of the master design is an orthogonal main effects design, which permits independent estimation of all effects of interest. Two 2-level attributes were used to describe bus/busway and train/light rail modes, such that bus/train options appear in 36 scenarios and busway/light rail in 45.

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

SHORT (< 30 mins.)	**Car no toll**	**Car toll rd**	**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 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 destination from 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 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 destination from 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 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 destination from 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					

Table 2 Example of the Format of a Travel Choice Experiment Showcard

SA101	1. CAR, TOLL ROAD	2. CAR, NON-TOLL ROAD
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**

Empirical Results

Share profiles of RP and SP choices for each of the six cities and the overall totals for all six cities are summarised in Tables 3 and 4. Walk and 'other' were eliminated in the RP models because insufficient individuals chose "walk", and 'other' is uninformative. Tables 3 and 4 reveal that the RP modal shares are quite different from their stated counterparts; hence there would be little predictive value in trying to reproduce the stated choice shares, especially because the base is the position of comparison in a switching context. The latter point is particularly germane for deriving elasticities which require knowledge of choice probabilities.

Table 3(a): Profile of Revealed Preference Modal Share (%) - Chosen Main Mode

	CAN	SYD	MEL	BRS	ADL	PER	TOTAL
Drive alone	52.0	51.0	62.4	50.0	54.3	61.4	55.3
Ride share	22.0	16.0	14.8	26.3	21.3	17.4	19.4
Bus	19.5	7.4	1.3	7.2	11.6	9.2	8.3
Train	0.0	19.8	13.5	11.0	3.0	7.1	10.4
Walk	1.6	3.3	3.0	1.7	1.2	0.5	2.0
*Other	4.9	2.5	5.1	3.8	8.5	4.3	4.6
Total Number	123	243	237	236	164	184	1187

* "other" is taxi, ferry (in SYD, BRS), motorbike and bicycle

Table 3 (b): Profile of Revealed Preference Modal Share (%) - Alternative Main Mode

	CAN	SYD	MEL	BRS	ADL	PER	TOTAL
Drive alone	10.6	15.6	15.6	13.1	9.8	7.6	12.6
Ride share	22.8	21.8	21.5	24.6	25.0	24.5	23.3
Bus	41.5	23.0	15.6	24.6	28.0	28.8	25.4
Train	0.0	18.1	22.8	18.6	9.8	17.9	16.1
Walk	4.9	6.6	6.3	5.1	9.1	8.2	6.7
*Other	20.3	14.8	18.1	14.0	18.3	13.0	16.1
Total Number	123	243	237	236	164	184	1187

* "other" is taxi, ferry (in SYD, BRS), motorbike and bicycle

Table 4: 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 the number of cars in household to number of workers.

Table 5 contains the final model for stand-alone SP, stand-alone RP and rescaled RP using a sequentially derived set of SP attribute taste weights. Table 6 displays the jointly estimated SP-RP HEV model with free variances. Table 7 contains the joint SP-RP 'nested logit' model with scale parameter normalised to 1.0 for RP and a single variance-scale ratio estimate across all SP alternatives. Finally, Table 8 presents the joint SP-RP 'nested logit' model with partitioning of alternatives guided by the HEV model variance profile.

Table 5: Simple Multinomial Logit, Sequential SP and rescaled RP, optimal lambda = 0.475

Attribute	Alternative(s)	SP parameter estimates (t-value) *	RP parameter estimates using choice-based weights (t-value)	Rescaled RP parameter estimates using choice-based weights (t-value)
In-vehicle cost	All	-.54834 (-8.12)	-.4697 (-4.31)	-.54834 (fixed)
Main mode time	DA, RS	-.06087 (-6.17)	.007539 (-1.03)	-.06087 (fixed)
Personal income	DA	.007949 (1.46)	-.01723 (-2.31)	.02033 (1.96)
Car availability index	DA	.33059 (2.16)	0.9477 (2.60)	1.1152 (2.5)
Main mode time	BS,TN,LR,BWY	-.07509 (-5.99)	-.009577 (-1.44)	-.07509 (fixed)
Access & egress mode time	BS,TN,LR,BWY	-.02927 (-4.56)	-.05872 (-3.46)	-.02927 (fixed)
Drive alone constant	DA	-.4213 (-1.12)	-.2752 (-.44)	0.7966 (2.14)
Ride share constant	RS	-.31343 (-1.08)	-1.331 (-2.77)	-.4791 (-2.14)
Train specific constant	TN	.22401 (1.19)	0.2405 (1.01)	-
Light rail specific constant	LR	.35496 (2.00)	-	-
Busway specifc constant	BWY	.01641 (.09)	-	-
Bus specific constant	BS	0	-	0.3866 (1.52)
Scale parameter		-	-	0.475
Sample Size		2016	672	1344
Log-likelihood at convergene		-2366.83	-266.30	-320.06
Pseudo-R^2		0.344	.710	0.654

Note: the RP choice set excludes light rail and busway system.
* Choice-based weights are meaningless for an SP model

Table 6: Joint Estimation of Heteroscedastic Extreme Value SP-RP model

Attribute	Alternative(s)	SP parameter estimates (t-value) *	RP parameter estimates based on choice-based weights (t-value)
In-vehicle cost	All	-.14604 (-1.94)	-.14604 (-1.94)
Main mode time	DA, RS	-.01995 (-1.86)	-.01995 (-1.86)
Personal income	DA	.002632 (0.79)	.002632 (0.79)
Car availability index	DA	0.17412 (1.65)	0.17412 (1.65)
Main mode time	BS,TN,LR,BWY	-.002997 (1.79)	-.002997 (1.79)
Access & egress mode time	BS,TN,LR,BWY	-.0047483 (-1.84)	-.0047483 (-1.84)
Drive alone constant	DA	6.6437 (1.21)	9.7134 (1.29)
Ride share constant	RS	6.9206 (1.25)	8.3335 (1.27)
Train specific constant	TN	6.5841 (1.20)	-
Light rail specific constant	LR	6.6781 (1.23)	-
Busway specifc constant	BWY	6.0799 (1.09)	-
Bus specific constant	BS	-	7.8315 (1.34)
Scale parameters:			
Lambda	DA	0.851 (2.10)	1.213 (1.92)
Lambda	RS	0.487 (1.97)	0.731 (1.54)
Lambda	BS	4.343 (1.78)	1.439 (1.99)
Lambda	TN	0.476 (1.89)	3.340 (1.76)
Lambda	LR	0.468 (1.77)	-
Lambda	BS	1.282 (fixed)	-
Sample Size	9408		
Log-likelihood at convergence	-1350.8		
Pseudo-R^2	.651		

* Choice based weights are meaningless for SP models

We used the λ's estimated from the HEV model to infer an appropriate nested logit hierarchy instead of assuming a tree structure in which all respective RP or SP choice set variances are identical but SP variances can differ from RP (Table 8). Please note that a given set of alternatives (eg, public transport modes) may not appear in the same branch; rather, the structure reflects an absence of information revealed by the variance of the random component. For example, the HEV model suggests that the largest unexplained variability occurs for bus in SP choice sets, with train in RP choice sets next. Ride share, train and light rail had similar variances in SP choice sets, suggesting that they should be assigned to the same branch. Thus, the suggested 'nested logit' structure from Table 7 is:Nest A= SPRS,SPTN,SPLR; Nest B = RPRS,SPDA; Nest C = RPDA, RPBS, SPBWY; and Nest D = RPTN, SPBS.

Table 7: Nested Logit Joint SP-RP – Standard with all RP inclusive value =1

Attribute	Alternative(s)	SP parameter estimates (t-value in brackets)*	RP parameter estimates based on choice based weights (t-value in brackets)
In-vehicle cost	All	-.2833 (-6.57)	-.2833 (-6.57)
Main mode time	DA, RS	-..02377 (-6.48)	-..02377 (-6.48)
Personal income	DA	.003176 (-1.96)	.003176 (-1.96)
Car availability index	DA	.19003 (3.70)	-
Main mode time	BS,TN,LR,BWY	-.033211 (-6.66)	-.033211 (-6.66)
Access & egress mode time	BS,TN,LR,BWY	-.01604 (-5.56)	-.01604 (-5.56)
Drive alone constant	DA	-.3052 (1.82)	.65907 (2.4)
Ride share constant	RS	.01359 (.11)	-.57755 (-2.28)
Train specific constant	TN	-.03136 (-.15)	-
Light rail specific constant	LR	.11692 (.68)	-
Busway specifc constant	BWY	.13257 (.81)	-
Bus specific constant	BS	-	-.13035 (-.62)
Scale parameters :		*Combined SP-RP:*	
λ	RP (all),		1.00
λ	SP(DA)	0.51 (6.95)	
λ	SP(RS)	0.40 (6.92)	
λ	SP(BS)	0.51(5.76)	
λ	SP(TN)	0.56(5.72)	
λ	SP(LR)	0.53(6.02)	
λ	SP(BW)	0.46(6.11)	
Sample size		9408	
Log-likelihood at convergence		-2647.5	
Pseudo-R^2		.569	

* : choice-based weights are meaningless for an SP model

Table 8: Nested Logit SP-RP - partitioning guided by HEV model variance profile			
Attribute	Alternative(s)	SP parameter estimates (t-value) *	RP parameter estimates based on choice-based weights (t-value)
In-vehicle cost	All	-.6831 (-9.58)	-..6831 (-9.58)
Main mode time	DA, RS	-.0699 (-6.08)	-.0699 (-6.08)
Personal income	DA	.006638 (1.40)	.006638 (1.40)
Car availability index	DA	0.6168 (4.05)	0.6168 (4.05)
Main mode time	BS,TN,LR,BWY	-.06278 (-5.91)	-.06278 (-5.91)
Access & egress mode time	BS,TN,LR,BWY	-.03796 (-6.98)	-.03796 (-6.98)
Drive alone constant	DA	-1.3821 (-3.13)	-.71558 (-1.35)
Ride share constant	RS	-.58842 (-1.83)	-2.462 (-4.47)
Train specific constant	TN	-.3096 (-.91)	-
Light rail specific constant	LR	-.1622 (-.48)	-
Busway specifc constant	BWY	-.4831 (-1.31)	-
Bus specific constant	BS	-	-.8771 (-1.63)
Scale parameters :		*Combined SP-RP:*	
Lambda	RP (DA, RS) SP (BW),	1.34 (7.42)	
Lambda	RP(RS) SP(DA)	1.55 (9.09)	
Lambda	SP(RS,TN,LR)	1.41 (8.45)	1.16
Lambda	RP(TN) SP(BS)	1.16 (7.11)	
Sample size		9408	
Log-likelihood at convergence		-2652.5	
Pseudo-R^2		0.577	
* Choice-based weights are meaningless for an SP model SetA=SPRS,SPTN,SPLR; SetB= RPRS,SPDA; SetC= RPDA, RPBS, SPBWY, SetD=RPTN, SPBS			

Table 9 contains the matrix of direct and cross elasticities for fare, fuel and line-haul travel time. Table 9 generally reveals that the mean estimates are systematically lower when the location scale parameter is free (subject to normalisation of one alternative for identification). In turn, this suggests that some unobserved effects exist which are confounded with time and cost when all variances are constrained to be equal (MNL form) or when variances are equal within subsets of alternatives (NL form). This result suggests that the extant literature on MNL and NL models may systematically overestimate the behavioural sensitivity of a population to changes in travel times and costs. This may explain why forecasts of switching activity between modes often predicted more switching than observed in real travel activities.

Using the HEV scale parameter results to inform estimation of an appropriate NL model yields weighted average elasticity estimates which do not reproduce the HEV results. Specifically, comparison of the traditional NL SP-RP with the HEV-informed specification suggests that the latter does not unambiguously produce elasticities closer to HEV than traditional NL. This is surprising, and suggests a need for further research into the extent to which the NL ‘trick’ can be used to replicate the more general HEV model results.

Another comparison of interest is Sequential SP-RP with FIML NL. The scale parameter for the sequential model is 0.475, but varies for the joint specification from 0.4 to 0.56. The unweighted average is 0.495, which is indeed close. Although this suggests that sequential and joint methods may produce the same scale parameters, unfortunately, the elasticities differ, and new modes (eg, light rail and busway) cannot be included in the Sequential SP-RP model estimation (no one chose them). They can be included in the Sequential model by rescaling all parameters including the busway-specific constant in the SP-stand alone model. The advantage of the joint NL approach is that new alternatives are accounted for directly in estimation. The differences in elasticities (inter alia) is attributable to exclusion of light rail and busway modes in the sequential model. The latter result is important as it reflects the information loss inherent in sequential methods, especially if new alternatives are included in SP choice sets. Indeed, we obtained Sequential SP-RP elasticities closer to traditional NL SP-RP by re-estimating the NL model after removing the subsample who chose the new alternatives. This follow-up estimation suggests that the differences may be due to the presence/absence of new alternatives. A summary of the direct elasticticities across the models is plotted in Figure 1.

Table 9. Direct and cross elasticities for Various models

Note: Direct elasticities are shaded.

	DA	DA	DA	DA	DA	DA	RS	RS	RS	RS	RS	RS
Fuel/Fare	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV
DA SP	-0.745	-	-	-0.474	-0.803	-0.648	0.19	-	-	0.161	0.239	0.166
DA RP	-	-0.087	-0.068	-0.046	-0.052	-0.101	-	0.036	0.033	0.015	0.022	0.037
RS SP	0.327	-	-	0.268	0.326	0.258	-0.899	-	-	-0.593	-1.032	-0.914
RS RP	-	0.122	0.102	0.047	0.07	0.137	-	-0.283	-0.233	-0.124	-0.175	-0.261
BS SP	0.278	-	-	0.023	0.306	0.249	0.167	-	-	0.015	0.181	0.137
BS RP	-	0.194	0.159	0.096	0.115	0.223	-	0.162	0.152	0.089	0.107	0.143
TN SP	0.289	-	-	0.276	0.323	0.256	0.172	-	-	0.172	0.19	0.25
TN RP	-	0.106	0.101	0.015	0.069	0.122	-	0.132	0.174	0.002	0.084	0.107
LR SP	0.263	-	-	0.262	0.292	0.246	0.159	-	-	0.162	0.173	0.22
LR RP	-	-	?	-	-	-	-	-	?	-	-	-
BWY SP	0.27	-	-	0.056	0.297	0.238	0.161	-	-	0.034	0.174	0.131
BWY RP	-	-	?	-	-	-	-	-	?	-	-	-
	DA	DA	DA	DA	DA	DA	RS	RS	RS	RS	RS	RS
Main Mode Time	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV
DA SP	-0.852	-	-	-0.572	-0.696	-.173	0.232	-	-	0.201	0.224	.056
DA RP	-	-0.023	-0.124	-0.088	-0.071	-0.161	-	0.009	0.054	0.026	0.027	0.054
RS SP	0.399	-	-	0.335	0.306	.085	-1.038	-	-	-0.720	-0.921	-.264
RS RP	-	0.032	0.172	0.085	0.09	0.203	-	-0.077	-0.439	-0.247	-0.252	-0.43
BS SP	0.308	-	-	0.029	0.258	.091	0.186	-	-	0.019	0.155	.054
BS RP	-	0.051	0.316	0.193	0.165	0.38	-	0.047	0.298	0.187	0.16	0.247
TN SP	0.332	-	-	0.328	0.279	.088	0.197	-	-	0.205	0.166	.095
TN RP	-	0.028	0.190	0.029	0.097	0.202	-	0.04	0.389	0.005	0.136	0.207
LR SP	0.29	-	-	0.306	0.243	.035	0.175	-	-	0.191	0.147	.036
LR RP	-	-	?	-	-	-	-	-	?	-	-	-
BWY SP	0.302	-	-	0.069	0.251	.044	0.181	-	-	0.041	0.151	.027
BWY RP	-	-	?	-	-	-	-	-	?	-	-	-

Table 9 continued

	BS	BS	BS	BS	BS	BS	TN	TN	TN	TN	TN	TN
Fuel/Fare	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV
DA SP	0.076	-	-	0.004	0.082	0.089	0.08	-	-	0.070	0.078	0.07
DA RP	-	0.039	0.032	0.030	0.026	0.089	-	0.034	0.016	0.001	0.025	0.043
RS SP	0.078	-	-	0.004	0.071	0.082	0.082	-	-	0.074	0.069	0.126
RS RP	-	0.125	0.112	0.104	0.085	0.082	-	0.148	0.095	0.003	0.103	0.166
BS SP	-0.551	-	-	-0.036	-0.565	-0.606	0.127	-	-	0.006	0.123	0.114
BS RP	-	-0.597	-0.507	-0.306	-0.408	-0.606	-	0.154	0.111	0.003	0.109	0.155
TN SP	0.138	-	-	0.005	0.143	0.148	-0.574	-	-	-0.307	-0.539	-0.589
TN RP	-	0.142	0.206	0.002	0.092	0.148	-	-0.631	-0.737	-0.023	-0.445	-0.729
LR SP	0.113	-	-	0.005	0.117	0.122	0	-	-	0	0	0.094
LR RP	-	-	?	-	-	0	-	-	?	-	-	-
BWY SP	0	-	-	0	0	0	0.104	-	-	0.019	0.097	0
BWY RP	-	-	?	-	-	0.122		-	?	-	-	-

	BS	BS	BS	BS	BS	BS	TN	TN	TN	TN	TN	TN
Main Mode Time	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV
DA SP	0.109	-	-	.001	0.115	0.088	0.13	-	-	.024	0.107	0.039
DA RP	-	0.01	0.048	0.010	0.031	0.049	-	0.008	0.021	0.000	0.027	0
RS SP	0.113	-	-	.001	0.094	0.08	0.132	-	-	.025	0.086	0.061
RS RP	-	0.029	0.170	0.031	0.108	0.137	-	0.037	0.144	0.001	0.133	0
BS SP	-0.83	-	-	-.009	-0.859	-0.62	0.235	-	-	.002	0.208	0.125
BS RP	-	-0.15	-0.814	-.097	-0.531	-0.672	-	0.054	0.240	0.001	0.2	0.181
TN SP	0.224	-	-	.002	0.243	0.163	-0.992	-	-	-.107	-0.819	-0.312
TN RP	-	0.037	0.399	0.001	0.143	0.165	-	-0.171	-1.224	-0.006	-0.602	-0.191
LR SP	0.174	-	-	.001	0.189	0.126	0.192	-	-	.000	0	0
LR RP	-	--	?	-	-	-	-	-	?	-	-	0
BWY SP	0	-	-	.000	0	0	-	-	-	.007	0.172	-
BWY RP	-	-	?	-	-	-	-	-	?	-	-	-

Table 9 continued

	LR	LR	LR	LR	BWY	BWY	BWY	BWY
Fuel/Fare	MNL-SP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV	MNL-SP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV
DA SP	0.102	0.094	0.105	0.093	0.093	0.020	0.109	0.097
DA RP	-	-	-	-	-	-	-	-
RS SP	0.105	0.098	0.093	0.157	0.096	0.020	0.095	0.088
RS RP	-	-	-	-	-	-	-	-
BS SP	0.15	0.009	0.15	0.133	0	0.007	0	0
BS RP	-	-	-	-	-	-	-	-
TN SP	0	0	0	0	0.139	0.022	0.153	0.132
TN RP	-	-	-	-	-	-	-	-
LR SP	-0.549	-0.301	-0.538	-0.558	0.173	0.028	0.189	0.162
LR RP	-	-	-	-	-	-	-	-
BWY SP	0.189	0.033	0.185	0.169	-0.573	-0.127	-0.629	-0.552
BWY RP	-	-	-	-	-	-	-	-

	LR	LR	LR	LR	BWY	BWY	BWY	BWY
Main Mode Time	MNL-SP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV	MNL-SP	HEV SP-RP	NL SP-RP TRAD	NL SP-RP HEV
DA SP	0.165	.032	0.142	0.105	0.137	.006	0.149	0.096
DA RP	-	-	-	-	-	-	-	-
RS SP	0.171	.033	0.118	0.157	0.141	.006	0.122	0.088
RS RP	-	-	-	-	-	-	-	-
BS SP	0.264	.003	0.246	0.157	0	.002	0	0
BS RP	-	-	-	-	-	-	-	-
TN SP	0	.000	0	0	0.212	.007	0.266	0.137
TN RP	-	-	-	-	-	-	-	-
LR SP	-0.931	-.103	-0.804	-.635	0.261	.009	0.312	0.167
LR RP	-	-	-	-	-	-	-	-
BWY SP	0.335	.012	0.308	0.202	-0.857	-.038	-0.957	-0.56
BWY RP	-	-	-	-	-	-	-	-

a. MNL Stated Preference and Revealed Preference (Sequential Estimation and rescaling) Note: Although the cross elasticities under the constant variance assumption are independent of the specific alternative, the probability weighted aggregate cross elasticities vary. Ben-Akiva and Lerman (1985, 113) show that the ‘ uniform disaggregate elasticities that result from the IIA property need not hold at the aggregate level’ .

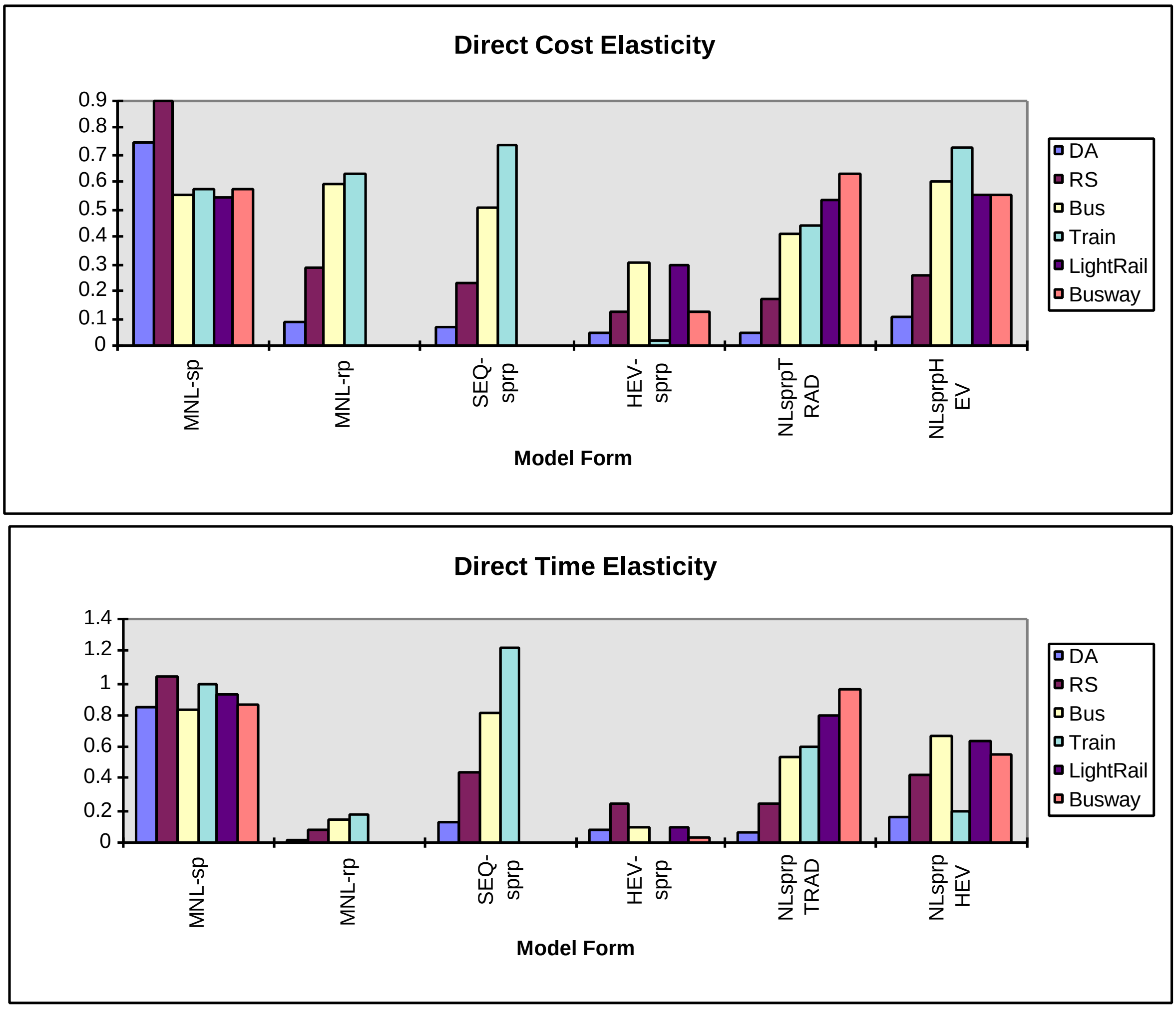

Figure 1. Direct Price and Time Elasticities

Conclusions

The empirical evidence presented in this paper highlights the magnitude of potential predictive 'error' than can be attributed to simplifications of the distributional properties of the random component of the indirect utility expressions in discrete choice models. That is, we found that mean estimates of the direct and cross elasticities for fare, fuel and line-haul travel time were systematically lower when location scale parameters were subject to normalisation of one alternative. In turn, this suggests that unobserved effects may be confounded with time and cost if all variances are constrained to be equal (MNL) or equal within subsets of alternatives (NL). More importantly, this also implies that MNL and NL models systematically *may* overestimate the sensitivity of populations to changes in travel times and costs, which also could account for the observation that such models often predicted more modal switching than has been observed in real markets.

We also investigated the use of HEV model scale parameter results to specify an appropriate NL model. Unfortunately, our results suggest that the resulting weighted average elasticity estimates do not accord with the HEV results. In particular, we found that the HEV-informed specification elasticities conformed no closer to HEV elasticities than those obtained from a traditional NL SP-RP estimation. While disappointing, this latter finding suggests that more research is needed into the extent to which one can specify a more informed NL model that can replicate the more general HEV model elasticities.

We also compared Sequential SP-RP with FIML NL, and found that the scale parameters of the sequential and joint models were close, but unfortunately elasticities differed significantly. The elasticity differences were due to exclusion of light rail and busway in the sequential model, which matters because it reflects information losses associated with sequential methods. The latter is especially important when new alternatives (eg, light rail and busway) are varied in SP choice sets because one cannot include them in Sequential SP-RP models as they are not chosen by anyone. Thus, the joint NL approach has a significant advantage in that new alternatives can be directly included in estimation. Further support for the superiority of joint NL is given by the finding that we obtained Sequential SP-RP elasticities closer to traditional NL SP-RP ones when we re-estimated the NL model after removing the sub-sample who chose the new alternatives. The latter result suggests that differences may be due to presence/absence of new alternatives, which should be the subject of future investigation.

In summary, therefore, our results suggest that caution should be exercised in using elasticity results from simplistic travel choice model specifications. More research clearly is needed into the behavioural appropriateness of more complex and realistic specifications like HEV, which relax the IID constant variance assumption of MNL or the slightly more relaxed assumptions of NL. As well, HEV places less a priori demands on the analyst to know or identify the correct specification for NL, but this relaxation comes at an increase in computational complexity and the lack of a simple closed-form for the probabilities. Our research also suggests that there are significant limitations in sequential estimation methods, which may not have been well-appreciated in previous applications, the most obvious of which is the inability to introduce new alternatives from SP in joint SP-RP estimation. Our results highlight the need for more process-oriented research to better understand the nature of these choice processes and develop more accurate specifications of same. In turn, this suggests that SP methods can serve a more informative role than merely to provide more stable estimates and/or introduce new alternatives. Rather, SP can play a focal role in understanding process better through experiments specifically designed to provide insights into process and/or utility specification. Unfortunately, these experiments necessarily will be more sophisticated and complex than SP experiments traditionally used in transport in the past. The wide disparity in elasticity estimates produced in our study, however, clearly suggests that better and more accurate models are needed, which requires more focus on process and less on prediction. Hopefully, this paper will be seen as a call for such research.

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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:		To your destination:	
Walk	1	Walk	1
Car/bus	2	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

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.

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