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A COMPARISON OF ELASTICITIES DERIVED FROM MULTINOMIAL LOGIT, NESTED LOGIT AND HETEROSCEDASTIC EXTREME VALUE SP-RP DISCRETE CHOICE MODELS

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Abstract

The literature on choice modelling offers limited evidence on the variations in 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 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. The evidence herein suggests that constraining the variance of the unobserved effects tends to over-estimate the elasticities sufficiently to distort the behavioural sensitivity of attributes influencing choice.

INTRODUCTION

Much progress has been made in understanding individual travel behaviour in the context of the utility maximisation paradigm, which mainly has been applied to discrete choice, revealed preference (RP) data. More recently, there also has been progress in extending this paradigm to include the use of stated choice (SC) data to enrich model estimation, (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, 1998a). Thus, recognition also is growing that benefits can be realised by fusing complementary sources of preference and choice data, which has coincided with advances in relaxing some assumptions of basic multinomial logit (MNL).

Specifically, different variances may be associated with unobserved random effects in complementary data sets (MNL imposes constant variances). In turn, this leads to (constant) scale parameters for all observed attributes. If scale parameters are not constant, this must be taken into account or attribute taste weights will be confounded with scale. In the case of MNL, one must rescale each data set to insure comparability of taste weights, and transfer information between data sets. General rescaling procedures now allow one to derive unique scale parameters for each alternative within and between data sets. The purpose of this paper is to compare and assess the implications of direct and cross price travel time choice elasticities estimated from three models that have different scale implications: 1) Sequential MNL (SMNL) 2) FIML 'Nested Logit' (FNL) and 3) Joint Heteroscedastic Extreme Value (HEV).

This paper is organised as follows. We first discuss the rationale for rescaling and outline approaches used to estimate scale parameters to obtain appropriate elasticity estimates. Next, we discuss the empirical context and study example, emphasising designed choice experiments. Then we present our empirical results comparing estimated elasticities and values of time savings. The paper concludes with a summary of our major findings.

Relaxing the constant variance assumption

The β parameter of each attribute in the indirect utility expression for an alternative reflects its contribution to variation in the level of relative utility. Each β is the product of a scale parameter and a taste weight parameter. In the MNL case, the scale parameter (hereafter λ) indexes variability in unobserved effects (and can be set = 1.0 arbitrarily). Simple MNL assumes that λ is independent of alternatives in choice sets; so does not affect comparisons of values *across* alternatives (McFadden 1981). This assumption often may be unsatisfactory. For example, if the unobserved effects of public transport options have higher variances than auto options, a constant variance assumption can overestimate the value of travel time savings for public transport use relative to automobile use.

Relaxing constant variance assumptions requires more complex models like HEV. Allenby and Glinter (1995), Bhat (1995) and Hensher (1997, 1998) provide recent examples of HEV model applications. The behavioural choice rule for the HEV model can be characterised as follows:

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

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

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 $1/\lambda$ ($\lambda^2 \propto 1/\sigma^2$ of the random component 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.

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

HEV allows differential cross-elasticities among all pairs of alternatives, such that two options have the same elasticity only if both scale parameters 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, 1998):

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

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 by equation (5)

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

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

$$\eta_{x_{km}}^{P_i} = \left[\frac{\partial P_i}{\partial V_m} / P_i\right] * \beta_k * x_{km}, \tag{6}$$

where β_k is the estimated taste weight on the kth variable.

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

$$\eta_{x_{ki}}^{P_i} = \left[\frac{\partial P_i}{\partial V_i} / P_i\right] * \beta_k * x_{ki}. \tag{7}$$

Bradley and Daly (1992) (and others) have used nested logit (NL) to estimate the values of scale parameter(s) to pool RP and SP data sources. NL allows scale parameter differences within and between SP and RP data sources, which is a convenient way to estimate scale parameters as inclusive value (IV) parameters, although estimates of λ's are unbounded. IV parameters allow different cross-substitution elasticities, unlike MNL. The elasticity formulae for NL 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 MNL elasticities for any alternative m in a non-nested partition of the tree. If m is in a partitioned part of the tree, the formula is modified to accommodate correlation between alternatives *within* a branch, as follows:

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

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

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

Even if the λ's for each branch do not differ statistically from 1.0, a tree structure may not be correct statistically and/or behaviourally. Instead, several trees should be evaluated, and if the λ's differ from 1.0, log-likelihoods of each tree should be compared using likelihood ratio tests: the tree exhibiting the lowest log-likelihood and better statistical fit then would be the preferred model.

In general, there are 2^M possible combinations of elemental alternatives without a structured partitioning process. Thus, one must use a priori critieria to partition alternatives initially, a key criterion being expected correlations between the random components of alternatives in each subset. HEV models potentially can help identify promising tree structure(s), thereby avoiding laborious examination of many potential tree structures.

THE EMPIRICAL STUDY

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 (Hensher et al 1995; Louviere, et al. 1994). The full choice set included currently available modes plus two 'new' modes (light rail and busway). Respondents chose among commuting options between their home and workplace locations in designed scenarios that varied different levels of policy-sensitive attributes so as to observe and model their coping strategies in each scenario.

Four alternatives appeared in each choice scenario: a) car (no toll), b) car (toll), c) bus or busway, and d) train or light rail. Showcards were used to describe 12 different 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. The public transport pairs evaluated by each respondent was determined by an experimental design (attribute levels summarised in Table 1). Accompanying contextual questions are available from the authors on request.

Five 3-level attributes described public transport alternatives (attribute definitions available from the authors on request): a) total in-vehicle time, b) frequency of service, c) closest stop to home, d) closest stop to destination and e) fare. Attributes of 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 us to estimate alternative-specific main effects for each mode (car no toll; car toll road; bus; busway; train; light rail), and alternative-specific linear x linear 2-way interaction effects for both car modes and generic (interaction) effects for bus/busway and train/light rail modes.

Scenarios were made from a 27 x 3^{27} factorial: an orthogonal fraction was used to make 81 choice sets (the 27-level factor created 27 versions of three pairs of alternatives). An orthogonal fraction of the 3^{27} insured independent estimation of the aforementioned effects. This design resulted in bus/train options appearing in 36 scenarios and busway/light rail in 45.

EMPIRICAL RESULTS

Table 2 summarises the final models for stand-alone SP, stand-alone RP and rescaled RP using a sequentially derived set of SP attribute taste weights. Table 3 displays the jointly estimated SP-RP HEV model with free variances. Table 4 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 5 presents the joint SP-RP 'nested logit' model with partitioning of alternatives guided by the HEV model variance profile.

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 - Simple multinomial logit, sequential sp and rescaled rp, optimal lambda = 0.475

Attribute	Alternative(s)	SP estimates (t-value) **	RP estimates (t-value)*	Rescaled RP estimates (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: RP choice set excludes light rail and busway system. *Based on choice-based weights; ** Choice-based weights are meaningless for an SP model

Table 3 - Joint estimation of heteroscedastic extreme value SP-RP model

Attribute	Alternative(s)	SP estimates (t-value) **	RP estimates (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		

*Based on choice-based weights; ** Choice based weights are meaningless for SP models

Table 4 - Nested logit joint SP-RP – standard with all RP inclusive value =1

Attribute	Alternative(s)	SP estimates (t-value)**	RP estimates (t-value)*
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:*	

Table 4 - continued

Attribute	Alternative(s)	SP estimates (t-value)**	RP estimates (t-value)*
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 used in estimation; ** choice-based weights are meaningless for an SP model

Table 5 - Nested logit SP-RP - partitioning guided by HEV model variance profile

Attribute	Alternative(s)	SP estimates (t-value) **	RP estimates (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 used in estimation; ** choice-based weights are meaningless for an SP model
SetA=SPRS,SPTN,SPLR; SetB= RPRS,SPDA; SetC= RPDA, RPBS, SPBWY, SetD=RPTN, SPBS

HEV λ's were used to infer an appropriate NL hierarchy (Table 5). In this case NL reflects an absence of information revealed by the random component variances: eg, results suggest SP Bus has the largest unexplained variance, followed by RP train. SP Ride share, train and light rail have similar variances, suggesting assignment to the same branch (Thus, Table 3 suggests Nest A= SPRS,SPTN,SPLR; Nest B= RPRS,SPDA; Nest C= RPDA,RPBS,SPBWY; Nest D= RPTN, SPBS).

Table 6 contains the direct and cross elasticities for fare, fuel and line-haul travel time, which generally reveal that mean estimates are systematically lower if the λ's are free (normalised on one alternative for identification). In turn, this suggests that some unobserved effects are confounded with time and cost if all λ's are constrained equal (MNL) or if λ's are equal within subsets of alternatives (NL). This also suggests that the literature on MNL and NL models may systematically overestimate behavioural sensitivities of populations to changes in travel times and costs, which may explain why between-mode switching forecasts often over-predict switching compared with real travel activities.

NL models suggested by HEV scale parameter results yield weighted average elasticity estimates that do not reproduce the HEV results. That is, comparing a traditional NL SP-RP to an HEV-informed NL model suggests that the latter need not yield elasticities closer to HEV than traditional NL. This is surprising, and suggests a need for further research to explain this disparity.

Table 6 - 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-HEV SP-RP	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL-HEV SP-RP
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-HEV SP-RP	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL–HEV SP-RP
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 6 - 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-HEV SP-RP	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL-HEV SP-RP
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-HEV SP-RP	MNL-SP	MNL-RP	SEQ SP-RP	HEV SP-RP	NL SP-RP TRAD	NL-HEV SP-RP
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 6 - continued

	LR	LR	LR	LR	BWY	BWY	BWY	BWY
Fuel/Fare	MNL-SP	HEV SP-RP	NL SP-RP TRAD	NL-HEV SP-RP	MNL-SP	HEV SP-RP	NL SP-RP TRAD	NL-HEV SP-RP
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-HEV SP-RP	MNL-SP	HEV SP-RP	NL SP-RP TRAD	NL-HEV SP-RP
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'.

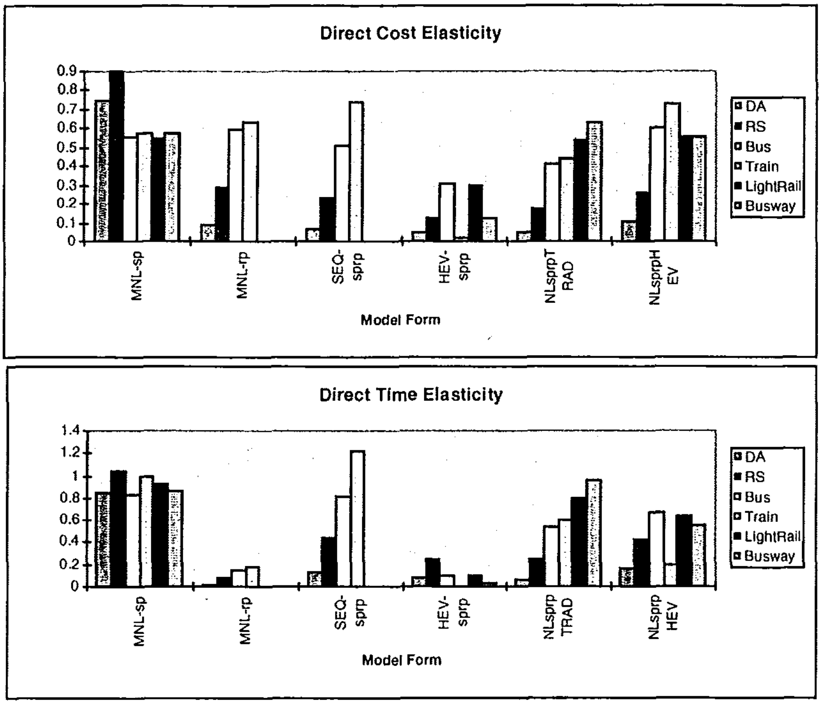

Figure 1 - Direct price and time elasticities

Also of interest is variation in the λ estimate for sequential SP-RP; λ for sequential SP-RP = 0.475, but varies from 0.4 to 0.56 for joint models. The unweighted average is 0.495, which although close unfortunately produces different elasticities, and new modes (eg, light rail and busway) cannot be included in the Sequential SP-RP 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 FIML-NL approach is that new alternatives are accounted for directly in estimation, and the elasticity differences (inter alia) can be attributed to exclusion of light rail and busway in the sequential model. The latter result 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 choosing the new alternatives, which suggests that differences may be due to the presence/absence of new alternatives. Direct model elasticities are summarised in Figure 1.

CONCLUSIONS

The empirical evidence in this paper suggests considerable differences in potential magnitudes of predictive 'errors' may be due to simplifications of distributional properties of random components of 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 if scale parameters were subject to normalisation of one alternative. In turn, this suggests that unobserved effects may be confounded with times and costs if all variances are constrained to be equal (MNL) or equal within subsets of alternatives (NL). Moreover, MNL and NL models *may* overestimate the sensitivity of populations to changes in travel times and costs *systematically*, which may account for observations that such models often predict more modal switching than is observed in real markets.

We also examined if HEV model scale parameter results help to specify NL models. Unfortunately, we found that weighted average elasticity estimates do not match HEV; and in fact, HEV-informed NL specification elasticities were no closer to HEV elasticities than those from traditional NL SP-RP estimation. 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.

Comparison of Sequential SP-RP with FIML-NL revealed similar scale parameters for sequential and joint models, but different elasticities. Elasticity differences were due to exclusion of light rail and busway in sequential models, which reflects a loss of information in sequential methods. The latter is especially important if new alternatives (eg, light rail, busway) are varied in SP choice sets because they cannot be included in Sequential SP-RP models (they are not chosen), which confers a clear advantage to joint NL (new alternatives can be included directly in estimation). Another advantage of joint NL comes from our finding that Sequential SP-RP elasticities are closer to traditional NL SP-RP ones if NL models are re-estimated removing sub-samples who chose new alternatives. In turn, this suggests that differences may be due to presence/absence of new alternatives, which should be the subject of future investigation.

In summary, our results suggest caution in using elasticity results from simple model specifications, but we need more research into the appropriateness of more complex and realistic models like HEV. Although HEV imposes less demands on analysts to know or identify correct NL specifications, it also increases computational complexity and has no simple closed-form for probabilities. We also found possibly significant limitations to sequential estimation, which do not seem to have been widely-appreciated previously; an obvious limitation being the inability to introduce new alternatives from SP in joint SP-RP estimation. Our results suggest a need for more process-oriented research to better understand the nature of choice processes and develop more accurate models. As well, it would seem that SP methods could play a more informative future role other than helping to stabilise estimates and/or introduce new alternatives. Instead, SP should be able to help us better understand process via experiments specifically designed to provide insights into process and/or utility forms. However, such experiments necessarily must be more sophisticated and complex than those often used in transport. Indeed, the wide disparity in elasticity estimates produced in our study 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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