ITLS

The implications of respondent information processing rules on preference revelation in stated choice experiments

By

David A Hensher

January 2005

INSTITUTE of TRANSPORT and LOGISTICS STUDIES

The Australian Key Centre in
Transport and Logistics Management

The University of Sydney

Established under the Australian Research Council's Key Centre Program.

NUMBER:	Working Paper ITLS-WP-05-01

TITLE: **The implications of respondent information processing rules on preference revelation in stated choice experiments**

ABSTRACT: Individual's process the information in stated choice (SC) experiments in many different ways. In order to accommodate decisions rules that are used in processing information, there is good sense in conditioning the parameterisation of stated choice design attributes on these rules. In particular, rules might be invoked to cope with the dimensionality of the SC design. The information processing strategy (IPS) can act as a qualifier of heterogeneity in the mean and/or heteroscedasticity of the distribution of the marginal (dis)utility of design attributes. In this paper we investigate the impact of rules such as attribute aggregation and reference dependency on the mean and the standard deviation parameters to produce revised preference profiles for specific design attributes, as we vary the dimensionality of an SC design. By contrasting mixed logit models with and without IPS conditioning, we are able to establish the extent of parameter shift and the implications on outputs such as willingness to pay. The empirical evidence, drawn from a study in Sydney of car commuter route choice, suggests that accounting for the way that stated choice designs are processed, given their dimensionality, does make a statistically significant difference on the profile of preferences for specific attributes and alternatives. This evidence has value in guiding the design of SC experiments and in adjusting results from different SC designs when comparing the evidence.

KEY WORDS: *Stated choice designs, information processing, preference differences*

AUTHORS: David A Hensher

CONTACT: Institute of Transport and Logistics Studies (Sydney)
The Australian Key Centre in Transport and Logistics Management, (C37)
The University of Sydney   NSW   2006   Australia

Telephone:	+61 9351 0071
Facsimile:	+61 9351 0088
E-mail:	itsinfo@its.usyd.edu.au
Internet:	http://www.its.usyd.edu.au

DATE: January, 2005

1. Introduction

Individual's process the information in stated choice experiments in many different ways, in part as a response to the demands of the stated choice design and in part because of the relevancy of information in choice making. To accommodate decisions rules that are used in processing information, there is good sense in conditioning the parameterisation of stated choice design attributes on these rules, recognising that choice responses might be influenced by the dimensions of the design (e.g., number of attributes and alternatives, attribute range and levels), the use of 'adding up' attributes where this is feasible (e.g., travel time components – see Starmer and Sugden 1993) and reference dependency such as contrasts of attribute levels in the SC design relative to recent experiences.

The mixed logit model provides a framework within which we can condition the marginal (dis)utilities of attributes on the information processing rules of individuals. The built in randomness of the model parameters allow the researcher to incorporate both observed and unobserved heterogeneity of individuals. The information processing strategy (IPS) can act as an explanation of heterogeneity in the mean as well as the heteroscedasticity of the distribution of the marginal (dis)utility of design attributes. Received applications have built this heterogeneity into the means of the distributions of the random parameters, as well as the conditional variances of these distributions (e.g., Bhat 1998, 2000, Greene *et al*., 2004, and Hensher and Greene 2004).

In this paper, we summarily lay out the extended mixed logit model to allow for mean and variance heterogeneity, drawing of recent work by Greene *at al.* (2004). We then detail the design of a stated choice experiment, and present the results for the preferred models for commuter choice of a package of route-based trip attributes. By contrasting the empirical models with and without the IPS conditioning, we are able to establish the extent of parameter shift and the implications on outputs such as the valuation of travel time savings. The empirical evidence suggests that accounting for the way that stated choice designs are processed, given their dimensionality, does make a statistically significant difference on the profile of preferences for specific attributes and alternatives. This difference is accounted for via the variance of preferences in contrast to the influence of the design dimensions which qualifies the mean of the preference distribution.

2. Individual-specific information processing

Individuals bring to a stated choice study a set of information processing rules that incorporate the processing and selection rules learnt through choice experience accumulated (and discounted) from the past. Processing rules are typically drawn on to accommodate relevance and complexity (Hensher 2004a,b; Starmer 2000; Swait and Adamowicz 2001a,b; Malhotra, 1982). They include the use of reference dependency (i.e., framing, see Rolfe and Blamey 2001) as a way of establishing relative net benefit of 'new' alternatives or attributes packages, attribute preservation or elimination (including subtleties of inattention due to irrelevance or cognitive burden), and consequentiality (i.e., questions that have associated with them real reasons for the

1

individual to treat them as of consequence – see Carson *et al.* 2003). Assumptions that all individuals use the same IPS when evaluating stated choice experiment treatments run the real risk of imposing substantial biases on parameter estimates in choice models (see Hensher 2004a for some evidence)[1]. The variability in processing is often defined by constructs such as habit formation (e.g., Aarts and Dijksterhuis 2000, Aarts *et al.* 1997) and variety seeking (e.g., Khan 1995), both of which suggest mechanisms used to satisfy the individual's commitment of effort and cognitive abilities. If we knew what role these constructs played in behavioural response then we could design an SC experiment tailored to a specific IPS.[2]

Arentze *et al.* (2003) scrutinised the influence of task complexity in terms of the number of attributes, alternatives and choice sets presented, as well as the influence of presentation format (surveys with or without pictorial material) including the effects of considering a less literate population. They found that both the presentation method and the literacy level had no significant impacts, while task complexity had a significant effect on data quality.

SC designs have in the main assumed that all attributes are processed in what DeShazo and Fermo (2004) describe as the *passive bounded rationality* model wherein they attend to all information in the choice set but increasingly make mistakes in processing that information. Contrasting this is the *rationally-adaptive* model that assumes individuals recognise that their limited cognition has positive opportunity costs. As DeShazo and Fermo (2004) state: "Individuals will therefore allocate their attention across alternative-attribute information within a choice set in a rationally-adaptive manner by seeking to minimise the cost and maximise the benefit of information evaluation" (page 3).

In recognition of the diverse nature of processing of stated choice experiments, it is important to condition the preferences for attributes and alternatives, revealed within the experimental setting, by the dimensionality of the SC deign and other rules acquired by individuals to assist them in any choice setting. In the next section we show how these processing criteria can be built into the mixed logit model through deep parameterisation of the marginal (dis)utilities of attributes representing preferences.

3. Incorporating information processing rules in mixed logit[3]

We assume that a sampled individual q ($q=1,\dots,Q$) faces a choice among J alternatives in each of T choice situations. Individual q is assumed to consider the full set of offered alternatives in choice situation t and to choose the alternative with the highest utility. The utility associated with each alternative j as evaluated by individual q in choice

---

[1] Including false assumptions about lexicographic choice behaviour.

[2] Such a SC experiment has some similarities to an adaptive choice experiment in which alternative behavioural choice response segments are identified as a way of recognising decision rules such as 'hard-core loyal', 'brand-type', IIA-type and product or service form.

[3] This section draws on Greene *et al.* (2004).

situation *t,* is represented in a discrete choice model by a utility expression of the general form in (1):

$$U_{jtq} = \mathbf{b}_q' \mathbf{x}_{jtq} + \varepsilon_{jtq}, \tag{1}$$

where $\mathbf{x}_{jtq}$ is the full vector of explanatory variables, including attributes of the alternatives, socioeconomic characteristics of the individual and descriptors of the decision context and choice task itself in choice situation *t*. The components $\mathbf{b}_q$ and ε_{jtq} are not observed by the analyst and are treated as stochastic influences.

Individual heterogeneity is introduced into the utility function through $\mathbf{b}_q$. We allow the 'individual-specific' parameter vector to vary across individuals both randomly and systematically with observable variables, $\mathbf{z}_q$. In the simplest case, the parameters are specified as

$$\mathbf{b}_q \quad = \mathbf{b} + \mathbf{D}\mathbf{z}_q + \mathbf{S}^{1/2}\mathbf{v}_q$$

$$= \mathbf{b} + \mathbf{D}\mathbf{z}_q + \mathbf{h}_q. \tag{2}$$

or

$$\beta_{qk} \quad = \beta_k + \mathbf{d}_k'\mathbf{z}_q + \eta_{qk,}$$

where β_{qk} is the random coefficient for the kth attribute faced by individual *q*. $\mathbf{b} + \mathbf{D}\mathbf{z}_q$ accommodates heterogeneity in the mean of the distribution of the random parameters. The random vector $\mathbf{v}_q$ endows the random parameter with its stochastic properties. For convenience, denote the matrix of known variances of the random draws as $\mathbf{W}$. The scale factors which provide the unknown standard deviations of the random parameters are arrayed on the diagonal of the diagonal variance matrix, $\mathbf{S}^{1/2}$.

To introduce variance heterogeneity into the model, let $\mathbf{S}_q^{1/2} = \mathrm{Diag}[\sigma_{q1}, \sigma_{q2}, \ldots, \sigma_{qK}]$ where

$$\sigma_{qk} = \sigma_k \times \exp(\mathbf{q}_k'\mathbf{h}_q) \tag{3}$$

and $\mathbf{h}_q$ is a vector of *M* variables such as demographic characteristics that enters the variances (and possibly the means as well). This adds a $K \times M$ matrix of parameters, $\mathbf{Q}$, to the model whose k^{th} row is the elements of $\mathbf{q}_k$. With this explicit scaling, the full model for the variances is now

$$\mathrm{Var}[\mathbf{b}_q | \mathbf{W}, \mathbf{z}_q, \mathbf{h}_q] = \mathbf{F}_q = \mathbf{G}\mathbf{S}_q^{1/2} \mathbf{W}\mathbf{S}_q^{1/2} \mathbf{G}'$$

The conditional variance of any specific parameter is given in equation (4) as

$$\mathrm{Var}[\beta_{qk} | \mathbf{W}, \mathbf{z}_q, \mathbf{h}_q] = [\sigma_k \exp(\mathbf{q}_k'\mathbf{h}_q) \, w_k]^2 \times \mathbf{g}_k'\mathbf{g}_k \tag{4}$$

where w_k is the known scale factor $\mathbf{W}_{kk}^{1/2}$ and the covariance of any two parameters is

$$\mathrm{Cov}[\beta_{qk}, \beta_{ml}] = (\sigma_{qk} w_k)(\sigma_{qm} w_m) \times \mathbf{g}_k'\mathbf{g}_m \tag{5}$$

The *mixed logit* class of models assumes a general distribution for β_{qk} and an IID extreme value type 1 distribution for ε_{jtq}. That is, β_{qk} can take on different distributional forms. For a given value of $\mathbf{b}_q$, the *conditional* (on $\mathbf{z}_q$, $\mathbf{h}_q$ and $\mathbf{v}_q$) probability for choice j in choice situation t is multinomial logit, since the remaining random term, $\mathbf{e}_{jq}$, is IID extreme value:

$$\mathbf{P}_{jtq}(\text{choice } j \mid \mathbf{W}, \mathbf{X}_{tq}, \mathbf{z}_q, \mathbf{h}_q, \mathbf{v}_q) = \exp(\mathbf{b}_q \mathbf{x}_{jtq}) / \Sigma_j \exp(\mathbf{b}_q \mathbf{x}_{jtq}) \tag{6}$$

where the full set of attributes and characteristics is gathered in $\mathbf{X}_{tq} = [\mathbf{x}_{1tq}, \mathbf{x}_{2tq}, \ldots, \mathbf{x}_{Jtq}]$. For convenience, denote this as $P_{jtq}(\mathbf{b}_q \mid \mathbf{B}_{qt}, \mathbf{v}_q)$. Denote the marginal joint density of $[\beta_{q1}, \beta_{q2}, \ldots, \beta_{qK}]$ by $f(\mathbf{b}_q \mid \mathbf{W}, \mathbf{z}_q, \mathbf{h}_q)$ where the elements of $\mathbf{W}$ are the underlying parameters of the distribution of $\mathbf{b}_q$, ($\mathbf{b}, \mathbf{D}, \mathbf{G}, \mathbf{S}, \mathbf{Q}, \mathbf{W}$) and ($\mathbf{z}_q, \mathbf{h}_q$) are observed data specific to the individual that enter the determination of $\mathbf{b}_q$, such as socio-demographic characteristics. The density, itself, is induced by the transformation of the primitive random vector, $\mathbf{v}_q$ in $\mathbf{b}_q = \mathbf{b} + \mathbf{D}\mathbf{z}_q + \mathbf{G}\mathbf{S}_q^{1/2}\mathbf{v}_q$.

We label as the *unconditional* choice probability the expected value of the logit probability over all the possible values of $\mathbf{b}_q$, that is, integrated over these values, weighted by the density of $\mathbf{b}_q$ (it is still conditioned on the observable demographic information ($\mathbf{z}_q, \mathbf{h}_q$), but not on the unobservable $\mathbf{v}_q$). From (2), we see that this probability density is induced by the random component in the model for $\mathbf{b}_q$, $\mathbf{v}_q$ (Hensher and Greene, 2003). Thus, the unconditional choice probability is

$$\mathbf{P}_{jtq}(\text{choice } j \mid \mathbf{W}, \mathbf{X}_{tq}, \mathbf{z}_q, \mathbf{h}_q) = \int_{\mathbf{b}_q} P_{jtq}(\mathbf{b}_q \mid \mathbf{O}, \mathbf{X}_{tq}, \mathbf{z}_q, \mathbf{h}_q, \mathbf{v}_q) f(\mathbf{b}_q \mid \mathbf{O}, \mathbf{z}_q, \mathbf{h}_q) d\mathbf{b}_q \tag{7}$$

$$= \int_{\mathbf{v}_q} P_{jtq}(\mathbf{b}_q \mid \mathbf{W}, \mathbf{X}_{tq}, \mathbf{z}_q, \mathbf{h}_q, \mathbf{v}_q) f(\mathbf{v}_q \mid \mathbf{W}) d\mathbf{v}_q$$

where, once again, $\mathbf{b}_q = \mathbf{b} + \mathbf{D}\mathbf{z}_q + \mathbf{G}\mathbf{S}_q^{1/2}\mathbf{v}_q$. Thus, the *unconditional* probability that individual q will choose alternative j given the specific characteristics of their choice set and the underlying model parameters is equal to the expected value of the conditional probability as it ranges over the possible values of $\mathbf{b}_q$. The random variation in $\mathbf{b}_q$ is induced by the random vector $\mathbf{v}_q$; hence, that is the variable of integration in (7). The log likelihood function for estimation of the structural parameters is built up from these unconditional probabilities, aggregated for individual q over the T choice situations and the choices actually made:

$$\log L = \sum_{q=1}^{Q} \log \int_{\mathbf{v}_q} \prod_{t=1}^{T} P_{jtq}(\mathbf{b}_q \mid \mathbf{W}, \mathbf{X}_{tq}, \mathbf{z}_q, \mathbf{h}_q, \mathbf{v}_q) f(\mathbf{v}_q \mid \mathbf{W}) d\mathbf{v}_q \tag{8}$$

The log likelihood function in (8) cannot be evaluated because the integrals will not have a closed form solution. But, it can be approximated by simulation. The simulated log likelihood function is given in equation (9).

$$\log L_S = \sum_{q=1}^{Q} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} P_{jtq}(\mathbf{b}_{rq} \mid \mathbf{W}, \mathbf{X}_{tq}, \mathbf{z}_q, \mathbf{h}_q, \mathbf{v}_{rq}). \tag{9}$$

where $\mathbf{v}_{rq}$ is the rth primitive random draw from the marginal population that generates $\mathbf{v}_q$. Details on estimation of the parameters of the mixed logit model by maximum simulated likelihood may be found in Train (2003).

4. The design plan

The data are drawn from a larger study reported in Hensher (in press, 2004a) in which 16 stated choice sub-designs (Table 1) have been developed, embedded in one overall design, with each sub-design being used in surveying a sample of car commuter trips in Sydney in 2002. The data was collected specifically to investigate the influence of different SC designs on preference revelation; however the substantive application provides useful policy outputs on values of travel time savings that can be used to evaluate the benefits of tollroads which in large measure deliver substantial time savings over alternative non-tolled routes.

Each commuter evaluated one sub-design; however across the full set of stated choice experiments, the designs differed in terms of the number, range and levels of attributes, the number of alternatives and the number of choice sets. The combination of the dimensions of each design is often seen as the source of design complexity (Dellaert et.,al. 1999) and it is within this setting that we have varied the number of attributes that each respondent is asked to evaluate. The overall sample was built up by having an inbuilt random number generator that selected one of the sub-designs each time a respondent is interviewed.

Table 1: The Sub-Designs of the Overall Design

Number of choice sets	Number of alternatives	Number of attributes	Number of levels of attributes	Range of attribute levels
15	3	4	3	Base
12	3	4	4	Wider than base
15	2	5	2	Wider than base
9	2	5	4	Base
6	2	3	3	Wider than base
15	2	3	4	Narrower than base
6	3	6	2	Narrower than base
9	4	3	4	Wider than base
15	4	6	4	Base
6	4	6	3	Wider than base
6	3	5	4	Narrower than base
9	4	4	2	Narrower than base
12	3	6	2	Base
12	2	3	3	Narrower than base
9	2	4	2	Base
12	4	5	3	Narrower than base

The candidate attributes have been selected based on earlier studies (see Hensher in press, Ohler et.al. 2000). They are: free flow time (FFT), slowed down time (SDT), stop/start time (SST), trip time variability (TTV), toll cost (TLC), and running cost (RC) (based on c/litre, litres/100km). Given that the 'number of attributes' dimension has four levels, we have selected the following combinations of the six attributes, noting that the aggregated attributes are combinations of existing attributes:

- *designs with three attributes:* total time (free flow + slowed down + stop/start time), trip time variability, total costs (toll + running cost)

- *designs with four attributes:* free flow time, congestion time (slowed down + stop/start), trip time variability, total costs
- *designs with five attributes:* free flow time, slowed down time, stop/start time, trip time variability, total costs
- *designs with six attributes:* free flow time, slowed down time, stop/start time, trip time variability, toll cost, running cost

The specific SC design is three unlabelled alternatives that have attribute levels that pivot off the levels associated with a current car-commuting trip. The designs are computer-generated. They aim at minimising the correlations between attributes and maximising the amount of information captured by each choice set. We maximised the determinant of the covariance matrix, which is itself a function of the estimated attribute parameters (within the experimental design literature this is known as D-optimality). The design dimensions are translated into SC screens as illustrated in Figure 1.
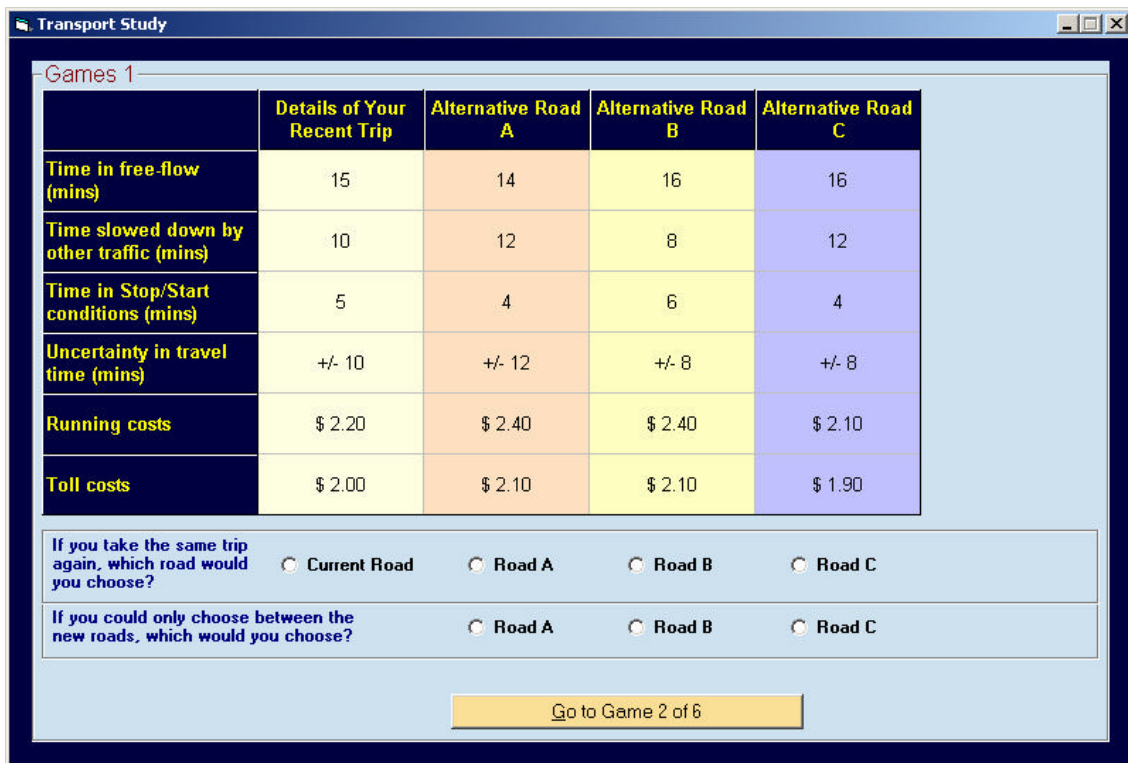

Figure 1:   Example of a stated choice screen

5. Results

Two empirical models are presented in Table 2, one when we do not parameterise the influence on the marginal (dis)utility of attributes of processing rules and SC design (ML1), and the other when we take this into account (ML2). The overall statistical fit of the two models is impressive. The likelihood ratio test, with a difference of five degrees of freedom between ML1 and ML2, rejects at the 95% confidence interval, the null hypothesis of no statistical difference.

A triangular distribution has been selected for the random parameters. The travel times, defined by two or three components, were estimated as random parameters in contrast to the travel cost and total time attributes, that were estimated as fixed parameters. The particular empirical estimates of willingness to pay are of passing interest[4] given the focus on the role of processing rules.

Table 2 Mixed logit models with alternative information processing conditions (4,593 observations). Time is in minutes, cost is in dollars. t-values in brackets except for values of time savings (which are standard deviations). 500 Halton draws.

Attribute	Alternatives	Mixed Logit 1 (ML1)	Mixed Logit 2 (ML2)
Random Parameters:			
Free flow time	2-4, 6-8, 10-12, 14-16, 18-20	-0.25027 (-17.22)	-0.26335 (-15.0)
Slowed time	3,4, 7,8, 11,12,15,16,19,20	-0.19729 (-16.49)	-0.20588 (-17.38)
Stop/start time	3,4, 7,8, 11,12,15,16,19,20	-0.19729 (-16.49)	-0.20588 (-17.38)
Slowed/stop/start time	2, 6,10,14,18	-0.19729 (-16.49)	-0.20588 (-17.38)
Fixed Parameters:			
Running cost	4,8,12,16,20	-0.97790 (-8.13)	-0.79285 (-7.92)
Toll cost	4,8,12,16,20	-1.6018 (-9.64)	-1.2358 (-9.03)
Total cost	1-3,5-7,9-11,13-15,17-19	-1.2394 (-15.48)	-1.28557 (-22.8)
Total time	5,9,13,17	-0.18431 (-20.68)	-0.18702 (-29.5)
Standard deviations of random parameters:			
Free flow time	2-4, 6-8, 10-12, 14-16, 18-20	0.71758 (12.86)	0.74710 (11.35)
Slowed time	3,4, 7,8, 11,12,15,16,19,20	0.31600 (6.85)	0.27873 (6.78)
Stop/start time	3,4, 7,8, 11,12,15,16,19,20	0.31600 (6.85)	0.27873 (6.78)
Slowed/stop/start time	2, 6,10,14,18	0.31600 (6.85)	0.27873 (6.78)
Heterogeneity around the mean random parameters:			
Free flow: wide attribute range	2-4, 6-8, 10-12, 14-16, 18-20		0.10539 (4.15)
Free flow: number of levels	2-4, 6-8, 10-12, 14-16, 18-20		0.02346 (3.82)
Slowed/stop/start time: # attributes	2-4,6-8, 10-12,14-16,18-20		0.01227 (4.69)
Heteroscedasticity in random parameters:			
Free flow : add time	2-4, 6-8, 10-12, 14-16, 18-20		-5.0536 (-5.61)
Free flow: reference dependency of free flow time	2-4, 6-8, 10-12, 14-16, 18-20		0.16707 (6.80)
Pseudo-R^2		0.716	0.719
Log-Likelihood		-3600.8	-3571.3
Value of travel time savings:			
Free flow time		15.43 (18.10)	14.41 (23.32)
Non-free flow time		12.14 (7.97)	10.97 (8.70)

Three design dimensions (number of attributes and levels, and attribute range) and two processing rules (aggregation and reference dependency) were found to be statistically significant qualifiers of specific travel time components. The design dimensions, interacted with the travel time attributes, all have a positive parameter estimate. This suggests, all other things being equal, that as we increase the number of attributes, the number of levels and the wider the attribute range, the marginal dis(utility) of the specific time attribute decreases. For a fixed cost parameter, the willingness to pay

---

[4] Estimates of valuation of travel time savings is usually limited to a single SC design. Furthermore one would normally expect the free flow values to be lower than the non-free flow values. The empirical values herein are not substantive given the nature of the design strategy.

(WTP) for free flow travel time *decreases* as the SC design adds levels and widens the offered set of absolute levels. The WTP for non-free flow time *decreases* as we add attributes. The evidence on attribute range reinforces the empirical position in other studies.

The most important finding in Table 2 is that processing rules influence the variance of particular parameters, in contrast to the mean; whereas the SC design influences the mean of the random parameters. This suggests that the great majority of stated choice studies which, at best, decompose the mean estimates, either through random parameter estimation or interaction with fixed parameters, are denied the opportunity to capture the rules that are used to process attributes.

When we take the evidence in Table 2 and derive the mean of the values of travel time savings (Table 3), we find some interesting trends. Most noticeably, as the SC design attribute level deviates further from the reference level, in either direction, the quartile mean VTTS increases (noting the mean VTTS for free flow time of $14.41). A negative level for the reference dependency of free flow time occurs when the SC level is less than the reference level. Thus we would conclude that SC designs in which the attribute levels deviate less from the reference (or experienced) level, are more likely to produce lower mean VTTS than those where the difference is greater.

Where an attribute has components that are potentially additive (as in components of travel time), we find that the mean VTTS is higher when a respondent evaluates the components via an addition rule. The application of such a rule does not necessarily suggest that the components are not distinguished, but rather that the components are assessed in the context of the total trip time. This distinction is subtle and potentially complex, requiring further research to understand exactly what is being processed. With 81 percent of the sample indicating that it evaluated the component of time within the context of adding them up, then this is an important issue to resolve. It should not however be assumed that future SC designs should simply offer a total travel time attribute, until we have convincing evidence that the differences in the marginal (dis)utilities associated with the components do not matter.

Table 3: Variation in VTTS attributable to SC design and IPS

Sub-sample	Number of attributes per alternative	Number of levels per attribute	# items (attributes * level)	Range of attributes	VTTS (mean, standard deviation) $ per person hour	
					Free flow time	Non-free flow time
Overall Sample VTTS						
					14.41	10.97
Design Dimensions						
		2	Wide		15.67	
		3	Wide		13.90	
		4	Wide		12.12	
		2	Not wide		16.47	
		3	Not wide		14.70	
		4	Not Wide		12.92	
	4					11.90
	5					10.97
	6					10.04
Add Time						
8373	Add time				14.75	11.10
1863	Not add time				15.14	11.26
Reference Dependency (range = -58 to +52 minutes) = SC level – reference level						
250	1st quartile	< -12			15.33	11.32
5211	2nd quartile	-12 to + 4			14.34	10.88
2521	3rd quartile	+5 to +10			14.80	11.20
2278	4th quartile	> 10			14.95	14.95

6. Conclusions

This paper is a contribution to a body of research centred on understanding the influence of the survey instrument in the revelation of the preferences of a sample of individuals when faced with evaluating a stated choice experiment and selecting their most preferred alternative. Evidence is accumulating to support trends in key behavioural outputs, such as willingness to pay, that can be attributed to systematic variations in the dimensions of the SC experiment.

These design dimensions induce (in part at least) specific processing rules as mechanisms for coping with the specification of the design (both quantitatively and qualitatively). However, and importantly, the behavioural responses may be associated with processing rules that individuals use in many circumstances that are not unique to processing SC experiments, and which are brought to bear on the SC task in hand.

The most revealing evidence is that processing rules have been identified through their qualification of the distribution of preference heterogeneity, in contrast to their influence on the mean of the distribution. We find, for example, that reference dependency does matter, and that any comparisons of results from two or more empirical studies that have not controlled for reference dependency can be problematic. The same inferences can be drawn for the dimensionality of a design; with lower mean estimates of VTTS associated with designs that have a wider range on each attribute, have a large number of attributes and a greater number of levels per attribute. The differences cannot be used to conclude that specific designs are 'better' than other designs in a relevancy sense. But they do send a very strong warning about comparing outputs from different stated choice studies.

References

Aarts, H & Dijksterhuis, A (2000) The automatic activation of goal-directed behaviour: the case of travel habit, *Journal of Environmental Psychology*, 20, 75-82.

Aarts, H, Verplanken, B & van Knippenberg, A (1997) Habit and information use in travel mode choices, *Acta Psychologica*, 96, 1-14.

Arentze, T, Borgers, A, Timmermans, H & Del Mistro, R (2003) Transport stated choice responses: effects of task complexity, presentation format and literacy. *Transportation Research* 39E, 229-244.

Bhat (1998) Accommodating Variations in Responsiveness to Level-of-Service Variables in Travel Mode Choice Modeling, *Transportation Research Part A,* 32 (7), pp. 495-507.

Bhat (2000) Incorporating Observed and Unobserved Heterogeneity in Urban Work Mode Choice Modeling, *Transportation Science*, 34 (2), pp. 228-238.

Carlsson, F & Martinsson, P (2003) Design techniques for stated preference methods in health economics, *Health Economics*, 12, 281-294.

Carson, RT, Groves, T & Machina, M (2003) Incentive and informational properties of preference questions, Department of Economics, University of California San Diego, March.

Dellaert, BGC, Brazell, JD & Louviere, JJ (1999) The effect of attribute variation on consumer choice consistency, *Marketing Letters*, 10, 139-147.

DeShazo, JR & Fermo, G (2001) Designing choice sets for stated preference methods: the effects of complexity on choice consistency, *Journal of Environmental Economics and Management*, 43 (3), 360-85.

DeShazo, JR & Fermo, G (2004) Implications of rationally-adaptive pre-choice behaviour for the design and estimation of choice models, working paper, School of Public Policy and Social Research, University of California at Los Angeles, August.

Gilboa, I & Schmeidler, D (2001) *A Theory of Case-Based Decisions*, Cambridge University Press, Cambridge.

Greene, WH, Hensher, DA & Rose, J (2004) Accounting for Heterogeneity in the Variance of Unobserved Effects in Mixed Logit Models, Department of Economics, Stern School of Business, New York University.

Hensher, DA (2004a) Accounting for Stated Choice Design Dimensionality in Willingness to Pay for Travel Time Savings, *Journal of Transport Economics and Policy*, 38 (2), 425-446.

Hensher, DA, Rose, J & Greene, W (2004b, in press) The Implications on Willingness to Pay of Respondents Ignoring Specific Attributes, Transportation.

Hensher, DA (in press) Revealing differences in behavioural response due to the dimensionality of stated choice designs: an initial assessment (ARC VTTS Grant 01-03) *Journal of Environmental Resource Economics*, Invited Paper (DoD#1).

Hensher, DA, Rose, J & Greene, WH (2005) *Applied Choice Analysis: A Primer*, Cambridge: Cambridge University Press.

Khan, BE (1995) Consumer variety-seeking among goods and services: An integrative review, *Journal of Retailing and Consumer Services*, 2 (3), 139-148.

Louviere, JJ, Hensher, DA & Swait, JF (2000) *Stated Choice Methods and Analysis*, Cambridge University Press, Cambridge.

Malhotra, N.K. (1982) Information load and consumer decision making, *Journal of Consumer Research*, 8, 419-430.

Ohler, T, Li, A, Louviere, J & Swait, J (2000) Attribute range effects in binary response tasks, *Marketing Letters*, 11, 3 249-260.

Rolfe, J, Bennett, J & Blamey, R (2001) Framing effects, in Bennett, J and Blamey, R. (eds), The Choice Modelling Approach to Environmental Valuation, Edward Elgar, Cheltenham, UK, 202-226.

Starmer, C (2000) Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk, *Journal of Economic Literature*, XXXVIII, 332-382.

Starmer, C & Sugden, R (1993) Testing for juxtaposition and event splitting effects, *Journal of Risk and Uncertainty*, 6, 235-54.

Swait, J & Adamowicz, W (2001a) The influence of task complexity on consumer choice: a latent class model of decision strategy switching, *Journal of Consumer Research,* 28, 135-148.

Swait, J & Adamowicz, W (2001b) Choice environment, market complexity, and consumer behavior: a theoretical and empirical approach for incorporating decision complexity into models of consumer choice, *Organizational Behavior and Human Decision Processes,* 49, 1-27.

Revelt & Train (2000) Customer-specific taste parameters and mixed logit, working paper, Department of Economics, University of California, Berkeley, http://elsa.berkeley.edu/wp/train0999.pdf

Train, K, (2003) *Discrete Choice Methods with Simulation*, Cambridge University Press, Cambridge.