

I T L S

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Reducing Sign Violation for VTTS Distributions through Recognition of an Individual's Attribute Processing Strategy

By

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1. Recognising the Behavioural Setting for Choice Making

"What lies ahead for discrete choice analysis? ... The potentially important roles of information processing, perception formation and cognitive illusions are just beginning to be explored and behavioral and experimental economics are still in their adolescence." (McFadden 2001)

Research in recent years has promoted the idea that the attributes influencing choice can be relevant or not relevant (Hensher 2006, in press, De Shazo and Fermo 2002). Deeming attributes as not relevant can be associated with cognitive and non-cognitive constraints (Berg 2005). Fundamentally, information is relevant if it contributes in a non-marginal way (i.e. beyond just noticeable difference) to payoff and that the benefits perceived to flow through from effort expended in accounting for that attribute exceed the costs.

Drawing on experimental findings from psychology and behavioural economics (e.g., Stroop 1935, Erber and Fiske 1984, Slovic 1995, Gilboa and Schmeidler 2001), we know that individuals often make incomplete use of available information, which implies that, although expected payoff functions may be influenced by specific attributes, an adopted information processing rule does not depend on these specific attributes. Such information processing rules are incomplete in the sense that human cognition provides filters¹ that result in adaptive responses to specific types of payoff/information environments. This is not the result of bounded rationality per se but the interaction of such rationality with the payoff-probability structure within the choice environment under study. *Hence ignoring attributes is a rational outcome of a choice process*. Bounded rationality in economics is typically given a narrow interpretation often linked to coping in a negative sense (or sub-optimal sense); whereas a more appealing interpretation credits it as an adaptive mechanism to support enhanced outcomes.

The stream of research by Hensher (Hensher 2004, 2006, in press) on accounting for the attribute processing strategy in stated choice² studies suggests that the existence of intuitively implausible signs for a part of a marginal disutility distribution (e.g. travel time) derived from random parameters in mixed logit models may be due, to some extent, to the manner in which the information is actually input into the estimation of the choice model. This is especially pertinent given the recent interest in the selection of the distributional assumptions, bounded or unbounded, symmetrical or asymmetrical, to capture taste heterogeneity that compensate for 'problems' with data (Hensher 2006a, Hess *et al*. 2005, 2006). .

In this paper we show evidence of what happens when we take into account a specific attribute processing strategy where respondents indicate that they ignored one or more attributes in making a choice. The findings suggest that significantly reducing the incidence of intuitively implausible values of travel time savings (VTTS) even with

1

¹ Enabling cognitive effort in general, and hence selective cognitive responses, to be allocated to the important tasks.

² This is also applicable to revealed preference data.

unconstrained distributions is linked to a recognition of attribute processing strategies adopted by respondents.

The remaining sections of the paper are organised as follows. The next section presents the empirical context and the design of the stated choice experiment that we use to estimate mixed logit models under the conditions of homogeneous and heterogenous attribute processing in respect of inclusion/exclusion and adding up. This is followed by the model results and the derivation of the properties of VTTS distributions for two analytical distributions – Rayleigh and normal. The paper concludes with a discussion of the implications of the findings.

2. Empirical Application

The data used to contrast models that do and do not account for the attention paid to each attribute is drawn from a study undertaken in Sydney in 2004, in the context of car driving non-commuters making choices from a range of level of service packages defined in terms of travel times and costs, including a toll where applicable. The sample of 223 effective interviews, each responding to 16 choice sets, resulted in 3,568 observations for model estimation.

To ensure that we captured a large number of travel circumstances, that will enable us to see how individuals trade-off different levels of travel times with various levels of tolls, we sampled individuals who had recently undertaken trips of various travel times, in locations where tollroads currently exist. To ensure some variety in trip length, three segments are investigated: no more than 30 minutes, 31 to 60 minutes, and more than 61 minutes (capped at two hours).

A telephone call was used to establish eligible participants from households stratified geographically, and a time and location agreed for a face-to-face computer aided personal interview (CAPI). A stated choice (SC) experiment offers the opportunity to establish the preferences of travellers for existing and new route offerings under varying packages of trip attributes. The statistical state of the art of designing SC experiments has moved away from orthogonal designs to D-optimal designs (see below and Rose and Bliemer 2004, Kanninen 2002, Bunch *et al.* 1996); and the behavioural state of the art has moved to promoting designs that are pivotted around the knowledge base of travellers (e.g., as in their current trip), in recognition of a number of supporting theories in behavioural and cognitive psychology and economics such as prospect theory, case-based decision theory and minimum-regret theory³ (Starmer 2000, p 353).

The two SC alternatives are unlabelled routes. The trip attributes associated with each route are summarised in Table 1. These were identified from reviews of the literature and through the effectiveness of previous VTTS studies undertaken by Hensher (2001).

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³ See Starmer 2000; Hensher 2004; Kahnemann and Tversky 1979a; Gilboa *et al*., 2002.

Table 1: Trip Attributes in Stated Choice Design

All attributes of the SC alternatives are based on the values of the current trip. Variability in travel time for the current alternative was calculated as the difference between the longest and shortest trip time provided in non-SC questions. The SC alternative values for this attribute are variations around the total trip time. For all other attributes, the values for the SC alternatives are variations around the values for the current trip. The variations used for each attribute are given in Table 2.

Table 2: Profile of the Attribute range in the SC design

	Free-flow time	Slowed down time	Variability	Running costs	Toll costs
Level 1	-50%	-50%	$+5%$	-50%	-100%
Level 2	- 20%	-20%	$+10\%$	-20%	$+20%$
Level 3	$+10\%$	$+10\%$	$+15%$	$+10%$	$+40%$
Level 4	+ 40%	+ 40%	$+20%$	$+40%$	$+60%$

The experimental design has one version of 16 choice sets. The design has no dominance given the assumptions that less of all attributes is better. The distinction between free flow and slowed down time is designed to promote the differences in the quality of travel time between various routes – especially a tolled route and a non-tolled route, and is separate to the influence of total time. Free flow time is interpreted with reference to a trip at 3 am in the morning when there are no delays due to traffic.⁴ An example of a stated choice screen is shown as Figure 1 with elicitation questions associated with attribute inclusion and exclusion shown in Figure 2. We use the response that includes the reference alternative, in model estimation.

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⁴ This distinction does not imply that there is a specific minute of a trip that is free flow per se but it does tell respondents that there is a certain amount of the total time that is slowed down due to traffic etc and hence a balance is not slowed down (i.e., is free flow like one observes typically at 3am in the morning).

	Details of Your Recent Trip	Road A	Road B			
	50	25	40			
Time slowed down by other traffic (mins)		12	12 ²			
Travel time variability (mins)		$+1 - 12$	$+1.9$			
	\$3.00	\$4.20	\$1.50			
	\$0.00	\$480	\$5.60			
	C Current Road	C Road A	G Road B			
		C Boad A	6 Road B			
For the chosen A or B road, HOW MUCH EARLIER OR LATER WOULD YOU BEGIN YOUR TRIP to arrive at your destination at the same time as for the recent trip: (note 0 means leave at same time) min(s) C earlier G later						
How would you PRIMARILY spend the time that you have saved travelling? C Stay at home C Shopping C Social-recreational C Visiting friends/relatives						
	Time in free-flow traffic (mins) If you make the same trip again, If you could only choose between the 2 new roads, which road would you choose?	10 $+1.10$				

Figure 1: An example of a stated choice screen

Figure 2: CAPI questions on attribute inclusion/exclusion

In determining the most statistically efficient design, the literature has tended towards designs which maximise the determinant of the variance-covariance matrix, otherwise known as the Fisher information matrix, of the model to be estimated. Such designs, known as D-optimal designs require explicit incorporation of prior information about the respondents' preferences. In determining the D-optimal design, it is usual to use the inversely related measure to calculate the level of D-efficiency, that is, minimise the determinant of the inverse of the variance-covariance matrix, known as D-error. A formal derivation is given in Rose and Bliemer (2004)

3. Model Results

The incidence of mixtures of attribute exclusion is given in Table 3. Just over half (i.e., 52 percent) of the sample attended to every attribute and not one respondent attended to none of the attributes. Running cost was the least attended to attribute when one attribute was ignored (i.e., 17.9 percent of the sample); in contrast the toll cost was attended to for 95.9 percent of the sample. Free flow time was not attended to by 13 percent of the sample, with 8.5 percentage point of this being when both components of travel time were ignored and the focus was totally on cost. The key message is that 78 percent of the sample attended to the components of travel time and 69 percent attended to the components of cost.

Attribute Processing Profile	Sample no. of observations=3568		
All attributes attended to $(v1)$	1856		
Attributes not attended to:			
Running cost $(v2)$	640		
Running and toll cost $(v3)$	192		
Toll Cost (y4)	96		
Slowed down time $(v5)$	192		
Free flow and slowed down time (v6)	304		
Free flow time $(v7)$	112		
Slowed down time and running cost $(v8)$	64		
Free flow and slowed down time and toll cost $(v9)$	48		
Adding up of Travel time	80.7%		

Table 3: Incidence of Mixtures of Attributes Processed

In mixed logit model estimation we condition each parameter on whether a respondent included or excluded an attribute in their attribute processing strategy. The observations are partitioned *before* estimation begins, and a different model is fit for those observations that do not use the specified attribute. The likelihood is computed separately for the two groups and the likelihood for the sample is the sum of the likelihoods for the groups.

Tables 4-6 present the model results for two analytical distributions to account for taste heterogeneity; the unconstrained Rayleigh and an unconstrained normal distribution. The full data set is used in all models. Model 1 does not account for whether a sampled individual indicated they had ignored an attribute throughout the experiment or not. Model 2 conditions the sample on attribute inclusion/exclusion. In addition to attribute inclusion/exclusion, we also estimated a model (under a Rayleigh distribution) (Model 3) in which we took into account whether free flow and slowed down time were aggregated in the evaluation process. We found that 80.7% of the sample added up these travel times. The model was re-specified so as to separate out inclusion/exclusion from additivity. The total time variable was relevant when the two attributes were added up and not ignored.

Models 1 and 2 are derived under the Rayleigh distribution, and hence attributes statistically significant under this condition may not be significant under other conditions (see below). Hensher (2006a) has shown that the Rayleigh distribution in its unconstrained and constrained forms has attractive properties. In particular it does not have the long tail that the lognormal exhibits and appears to deliver a relatively small proportion of negative VTTS when the function is not globally signed to be positive. The Rayleigh distribution probability function is given in (1) (Papoulis 1984, p. 148).

$$
P(r) = \frac{re^{-r^2/2s^2}}{s^2}
$$
 (1)

for $r \in [0, \infty)$, where s is the desired scale parameter. The mean is centred as s^{*} 2 $rac{\pi}{2}$ and the standard deviation is $\sqrt{\frac{4-\pi}{2}} s^2$. This distribution has a long tail, but empirically appears much less extreme than the lognormal. The random parameter estimates of the ML models were based on 500 Halton draws.

For both base models, all parameters associated with the design attributes are specified as generic random parameter estimates. With the exception of travel time variability, all parameters associated with the design attributes are statistically significant and of the expected sign. Comparison of models 1 and 2 (and 3) reveals significant differences in the parameter estimates of the models. Caution in interpretation however is required since we have estimated complex non-linear attribute functions and so to identify the full effect of a specific attribute, we must take into account all contributing sources aligned with the mean, the standard deviation and the sources of decomposition around the mean and the standard deviation parameter estimates. For example the full marginal (dis)utility effect of free flow time drawn unconditionally from the Rayleigh distribution for Model 1 is:

 $θ_q = {0.08933+.00160 x lead to improve pedestrian safety +0.1565 x exp[-0.0056 x trip kms] r}_q (2)$

Table 4: Summary of Empirical Results for Rayleigh Distribution, 500 Halton draws, 3568 observations

Table 5: Summary of Empirical Results for Normal Distribution, 500 Halton draws, 3568 observations

Table 6: Accounting for Attribute adding up and Inclusion/exclusion 500 Halton draws, 3568 observations

The results show the importance of accounting for heterogeneity in the mean of random parameters, and heteroscedasticity in these parameters via decomposition of the standard deviation parameter estimate⁵. The influences on heterogeneity around the mean are opinion variables, derived from a weighting of a response on a seven-point likert importance scale of the *importance* of such factors associated with toll roads in general and a seven point *'likely to deliver'* likert scale for specific tolled routes that respondents use. A positive parameter indicates, all other influences remaining fixed, that the opinion reflects something of greater importance and/or greater likelihood of it being delivered. For example, given that the mean estimate of the random parameter for slowed down time is negative and 'avoiding traffic lights' has a positive parameter estimate, the presence of a strong positive effect reduces the marginal (dis) utility of slowed down time.

All three random parameters are conditioned on the trip length in kilometres through decomposition of the standard deviation, with strong statistical significance, yet the sign changes with respect to slowed down time. All other effects being held constant, when combined with the standard deviation of the random parameter (all being positive as required), we see that as trip length increases the standard deviation decreases, resulting in reduced heterogeneity in preferences over longer trips. The exception is when all data is considered relevant for slowed down time, with preference heterogeneity increasing as trip length increases.

Seven variables have a statistically significant influence, in the base models, on the mean of the three random parameters when all attributes are included; but when we allow for attribution exclusion, for the same set of influences, three become statistically insignificant. In interpreting the parameter estimates for model 2, it is important to note that the estimates are specific only to sample population segments who consider an attribute whilst undertaking the choice experiment. For those who do not consider an attribute, the parameter estimate expression in (2) for that individual is zero. That is, the parameter estimates are specific to each attribute inclusion/exclusion strategy.

Willingness to pay distributions for travel time savings can be derived from the conditional parameter estimates obtained using methods outlined in Train (2003) and Hensher *et al.* (2005). One can construct such estimates by deriving the conditional distribution based (within-sample) on known choices (i.e., prior knowledge), as originally shown by Revelt and Train (2000). The values of travel time savings (VTTS) based on these estimated distributions are summarised in Table 7.

The incidence of negative VTTS under the unbounded Rayleigh and normal distributions in the presence and absence of the attribute processing strategy is summarised in Table 8. The main finding is that the absolute number (and hence percentage) of observations with negative VTTS *declines substantially* when we account for heterogeneity in the attribute processing strategy in respect of whether attributes (or attribute mixes) are ignored or taken into account and whether the travel time attributes (free flow and slowed down time) are aggregated or kept separate in processing. The incidence of negative VTTS when all attributes are assumed relevant, and there is no attribute adding up, varies from 5.1 percent for free flow under the normal distribution to 2.89 percent under Rayleigh for free flow and 2.3 percent for

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⁵ The base model in terms of selected specification of attributes is Model 1.

slowed down time under Rayleigh. When we account for attribute inclusion/exclusion, the incidence drops to zero in some cases (i.e., slowed down time under the normal distribution) and to a range from 0.64 to 0.76 percent for both attributes under either distribution (i.e. less than 1 percent). When we integrate attribute adding up together with inclusion/exclusion, the percent of negative VTTS is zero for free flow time, 0.87 percent for slowed down time and 0.48 percent for total time.

Given differences in variances of the VTTS distributions over Models 1 and 2 for each of the analytical distributions, for the same attribute, we conducted a Kruskall-Wallis test, which is the non-parametric equivalent to the ANOVA test (Siegel and Castellan, 1988). For the VTTS distributions obtained from the models, chi-square statistics were obtained for the free flow and slowed down time VTTS distributions, which we compared with a critical value of 5.99 (i.e., χ^2 at the 95 percent confidence level). We concluded that the means and variances of the VTTS distributions for both attributes are statistically different between the two models for both distributions. The VTTS distribution, when the APS is not accounted for, has a much greater range than when the attribute inclusion/exclusion strategy is accounted for.

Table 7: Values of travel time savings

		$R - All$	$R - APS$	R-APS-AGG	$N - AI$	$N - APS$
Free flow	number	103	25		182	27
	percent	2.89	0.70	0.00	5.10	0.76
Slow ed dow n	number	82	23	31		
	percent	2.30	0.64	0.87	0.00	0.00
Total time	number			17		
	percent			0.48		

Table 8: Incidence of negative VTTS

The behavioural implications suggest that a more careful account for the range of processing rules invoked in evaluating stated choice experiments (or any data set), appears to deliver behaviourally more plausible empirical evidence than offered by judicious selection of the analytical distributions alone. Behavioural appeal is more than the incidence of negative VTTS; it also relates to the overall profile of the full distribution. Table 7 shows a narrower range in general (the one exception being slowed down time under the normal) and a relative valuation between the two components of travel time that is intuitively more plausible. In particular, for the Rayleigh distribution, the ratio of the mean VTTS of slowed down to free flow time when APS heterogeneity is ignored is 0.989 and when APS heterogeneity is accounted for it becomes 1.27. The equivalent ratios for the normal distribution are 1.15 and 1.32. Inferentially we suggest that the APS strategy has a sensible influence on the behavioural outputs. When converted to time savings benefits in road projects, especially where investments are designed to reduce the levels of congestion, these differences would make a substantial difference to the user benefits, given the dominance of travel time savings. Such a conversion however requires knowledge of the incidence of each APS rule in the population.

4. Exploring the VTTS Distribution in more Depth

We can see much appeal in integrating more behavioural reality into the estimation of willingness to pay distributions, as well as continuing the inquiry into the 'behavioural' implications of specific analytical distributions, bounded and unbounded. We also recognise that the distributions herein, that have been deeply parameterized, contain systematic sources of taste variation as well as random taste heterogeneity, despite the fact that the latter is conditionally random in the sense of recognising the information in the choice (prior). When we look further into other possible sources of influence on the 'location' in the distribution we find, through a simple regression model of VTTS against contextual and socioeconomic characteristics, a number of sources of systematic variation.

To investigate the sources of influence on the sign of the marginal (dis)utility of time (and hence VTTS), we distinguish between three attribute processing contexts (i) individuals who did not exclude either attribute and added them up, (ii) the subset of individuals who did not add up the two attributes and included free flow time, and (iii) individuals who did not add up the two attributes and included slowed down time.

We found the following systematic evidence for a model in which the dependent variable is the 'signed VTTS', taking the value 1 for positive VTTS and 0 for negative VTTS. There were no negative VTTS (Table 8) for (ii) above. The t-ratios are reported in parenthesis after the estimated parameter.

Signed-VTTS (add up) = 5.373 (4.51) -0.0281 (-2.5) x trip distance (km) -1.659 (02.2) x gender (male = 1) + 0.0431 (2.2) x age, pseudo- r^2 = 0.082

Signed-VTTS (slowed down time) $=24.34$ (4.5) $+0.0032$ (2.4) x personal income – 0.131 (-4.2) x trip distance (km) +3.448 (4.1) x gender (male =1) -0.349 (-4.2) x age, pseudo- $r^2 = 0.237$.

The findings suggest that for total time, the probability of having a negative VTTS increases as the trip distance increases, the respondent is male and they are younger. For free flow time, the probability of having a negative VTTS increases as the trip distance increases, the respondent is female and they are older and have a lower personal income. To provide further insights we have identified the socioeconomic profile of the sample of individuals with positive and negative VTTS (Table 9), confirming the directional impact in the models.

Characteristic	Positive VTTS		Negative VTTS	
	Total time	Slowed down time	Total time	Slowed down time
Personal income (\$'000)	84.7 (38.3)	103.3(37.9)	80(18.7)	60.6(21.9)
Age	51.4 (11.9)	55.0(8.7)	44.5(4.3)	61.1(5.4)
Trip distance (km)	30.4 (17.6)	22.2(25.5)	41.3 (19.4)	25.0(8.2)
Gender $(1 = male)$	0.61	0.61	0.88	0.52
Number of observations	3023	289		31

Table 9: Profile of samples with positive and negative VTTS (based on R-APS-AGG) (standard deviation in brackets)

5. Conclusions

We have shown that accounting for individual specific information on attribute inclusion/exclusion results in significant differences in the parameter estimates and hence the willingness to pay for specific attributes in choice models. These differences arise from a form of respondent segmentation, the basis of which is respondent attribute processing. Through partitioning the log-likelihood function of discrete choice models based on the way that individual respondents process each attribute, the outputs of the models we estimate represent those of the attribute processing segments, rather than those of the entire sample population. In this way, we are able to detect the preferences for different segments within the sample population based on the attribute processing strategies existing within the sampled population. In traditional choice models, such segments will likely go undetected.

However, in applications of VTTS in project planning (e.g., predicting toll route patronage), it is necessary to identify the incidence of each APS in the relevant population of potential toll route users. The VTTS presented in Table 7 that account for APS will require an assumption on the incidence of specific APS's. Clearly the incidence of the APS linked to ignoring an attribute that is used to obtain the sample estimates herein may be different in specific applications; however re-weighting such VTTS for each segment is straightforward provided such weights are known⁶.

The evidence in this paper suggests that accounting for the way that attributes are processed makes a significant difference in terms of the distributional properties such as the incidence of negative VTTS and the behavioural plausibility of the distribution of positive VTTS.

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⁶ In the current study, the mean VTTS for free flow and slowed down time for each of the Rayleigh and normal distributions are, respectively \$18.89, \$24.96, \$15.31 and \$20.91 per person hour.

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