



WORKING PAPER

ITLS-WP-12-04

Inferring attribute non-attendance from stated choice data: Implications for willingness to pay estimates and a warning for stated choice experiment design.

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February 2012

ISSN 1832-570X

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-12-04

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ABSTRACT: There is a growing interest in traveller behaviour research to explore alternative information processing strategies (often referred to as heuristics or rules) adopted by individuals when assessing packages of attributes describing alternatives in a choice set, and making a choice. One popular attribute processing rule relates to attributes not being considered (i.e., being ignored), for all manner of reasons, referred to in the small but growing literature as attribute non-attendance or non-preservation. Researchers have used a mixture of methods to study the role of attribute non-attendance, including supplementary questions on whether each attribute is ignored or not, and methods in which the functional form of the utility expressions defining an alternative can recognise the possibility, up to a probability, of an attribute being ignored. Although supplementary questions are worthy of further consideration, despite the controversy as to the reliability of the response, recent interest has focused on ways to establish the incidence of attribute non-attendance without recourse to such evidence. In this paper we use an existing data set of choice amongst four attributes describing alternative car non-commuting trips, to illustrate the proposed method, and to compare values of travel time savings under each possible combination of non-attendance attributes relative to a model in which all attributes are assumed to be fully attended to. The paper reveals a major concern with the way that attribute levels and ranges are selected in the design of choice experiments, which can induce non-attendance situations where willingness to pay estimates cannot be obtained.

KEY WORDS: *Attribute processing; attribute attendance; toll vs. free routes; value of travel time savings; choice models; probabilistic decision process model.*

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Acknowledgements: We thank numerous individuals for suggestions arising from discussions and seminars, especially Stephane Hess, Ricardo Scarpa, Danny Campbell and Sean Puckett. The detailed comments and advice of referees have materially improved the paper, and we especially thank one referee who undertook an extensive editing of the paper.

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DATE: February 2012

1. Introduction

In a recent paper, Hess *et al.* (2011) state: “The study of respondent heterogeneity has been one of the main areas of research in the field of choice modelling in recent years. The emphasis has been on variations across respondents in the parameters used in the utility function while maintaining the assumption that the actual utility specification is generic across respondents. Recent work by David Hensher and colleagues has moved on from this by allowing for differences in the utility specification across respondents in terms of inclusion or otherwise of specific attributes, in the context of work looking at heterogeneous information processing strategies.” The manner in which attributes describing alternatives in discrete choice modelling settings are processed in order to form an outcome choice is now recognised as a worthy area of research.

There is a broad literature (*see* Gilovich *et al.* 2002) that encapsulates much of the progress in studying the role of heuristics and rules as aids in making decisions in real and hypothetical settings. The link to discrete choice modelling is in the process of preference construction, in other words, using specific rules and heuristics that are dependent on the choice environment. Heuristics can be associated with both the attributes of alternatives and with the alternatives defining a choice set, and they cover the broad spectrum of compensatory (i.e., all attributes being fully traded), and semi-compensatory rules (e.g., thresholds being imposed on the role of attributes in elimination-by-attributes forms – see Swait 2001, Cantillo and Ortuzar 2005, and Martinez *et al.* 2009 for examples in travel choice).

The focus in the current paper is on a very specific situation according to which respondents to a stated choice experiment adopt an attribute processing rule under which specific attributes are ignored (or “non-attended to” to use the terminology of some environmental economists), for all manner of reasons. Earlier efforts of Hensher *et al.* (2005, 2007), and Hensher (2006) highlighted the real possibility that such an attribute processing strategy does make a difference in estimates of willingness of pay for specific attributes (e.g., the value of travel time savings). Subsequent research by Hensher and Rose (2009), Hess and Hensher (2010) Scarpa *et al.* (2009, 2010), Campbell *et al.* (2010), and Puckett and Hensher (2008, 200) amongst others, has reinforced the view that accounting for “attribute non-attendance” does impact significantly on key behavioural outputs.

A number of the stated choice studies cited above, based their identification of attribute non-attendance on supplementary questions designed to establish whether a respondent had ignored an attribute or not: they could be asked either after each choice set or after completing all choice scenario assessments. However, as argued in a number of papers, such as Hensher and Rose (2009), Hess and Hensher (2010), and Hensher (2010), there is concern about the reliability of responses to such supplementary questions. Although the jury is still out on this issue, there is growing interest in the focus of this paper, i.e., identifying the role of attribute non-attendance through model inference, rather than directly asking each respondent. The most recent examples are Scarpa *et al.* (2010), Hess and Hensher (2010), Hensher and Greene (2010), and Hole (2010).

Hess and Hensher (2010) infer attribute processing strategies through the analysis of respondent-specific parameter distributions, obtained through conditioning on reported (or stated) choices. Their results suggest that some respondents do indeed ignore a subset of explanatory variables. There is also some evidence that these *inferred* attribute processing strategies are not necessarily consistent with the responses given to supplementary questions about attribute attendance. This raises questions about how both types of data can be used to assist in improving behavioural relevance. In a similar manner, Scarpa *et al.* (2009) implement two ways of modelling attribute non-attendance; the first involves constraining coefficients to zero in a latent class framework, while the second is based on stochastic attribute selection, and grounded in Bayesian estimation. In all studies, the results indicate that accounting for non-

attendance significantly improves model fit in comparison to models that assume full attribute attendance, and yields estimates of willingness to pay for specific attributes that are typically different.

Hess and Rose (2007), Hensher and Greene (2010) and Campbell *et al.* (2010) use a latent class framework as a way of capturing a probabilistic decision process, in which specific restrictions are imposed on the utility expressions for each class, to represent hypotheses of pre-defined attribute processing strategies. However, while a number of the classes relate to attribute non-attendance; these papers excluded the possibility of combinations of more than one attribute non-attendance rule. Investigating all combinations, while appealing, becomes increasingly complex and infeasible as the number of attributes (K) increases, given a 2^K rule for the combination of attendance or non-attendance. With four attributes, for example, we have 16 possible combinations, and with eight attributes we have 256. In this paper we study up to four attributes and hence 16 situations, within a modelling framework that allows for the inference of attribute non-attendance.

We infer the attribute processing strategy through the identification of up to 16 latent classes of attribute non-attendance, each associated with a particular combination. As a variant on the normal latent class framework (which we refer to as a probabilistic decision process model), we constrain each attribute's parameter estimate across classes to be the same, since we are interested in a single choice that conditions the outcome on the inferred attribute non-attendance rules. We illustrate the application of the method, comparing it with a multinomial logit (MNL) model that assumes full attribute attendance, using a data set collected in Sydney.

This paper is organised as follows. We set out the choice model in which attribute non-attendance is treated using latent classes; we then briefly describe the data, present the empirical analysis and interpret in the context of values of travel time savings (VTTS). We conclude with the major findings, highlighting the concern about choice experiments inducing situations where some attributes are not attended to, that results in the inability to estimate VTTS.

2. Attribute non-attendance: A probabilistic decision process model

Assume respondent $i = 1, 2, \dots, I$ is asked to select from amongst J alternatives, $j = 1, 2, \dots, J$. Assuming that the basic analytical framework is a standard MNL choice model, the probability that respondent i chooses alternative j is given as

$$\text{Prob}(i,j) = \frac{\exp(\beta' \mathbf{x}_{i,j})}{\sum_{j=1}^J \exp(\beta' \mathbf{x}_{i,j})} \quad (1)$$

where $x_{i,j}$ represents the attributes associated with alternative j as observed by respondent i and β' is a vector of parameter weights related to the attributes.

Non-attendance is accommodated by supposing that individuals sort themselves into one of 2^K (or $q=1, \dots, Q$) classes, distinguished by which of the attributes were considered in their choice process. If the configuration chosen by the individual is not directly observed (as, for example, in a supplementary question), then in the model, this sorting can only be done probabilistically. In the context of (1), we can model this by writing equation (2).

$$\text{Prob}(i,j|q) = \frac{\exp(\beta'_q \mathbf{x}_{i,j})}{\sum_{j=1}^J \exp(\beta'_q \mathbf{x}_{i,j})} \quad (2)$$

β_q is one of the 2^K possible vectors β in which m of the elements are zero and $K-m$ are nonzero. Specifically, q can be thought of as a masking vector of the form $(\delta_1, \delta_2, \delta_3, \delta_4, \dots)$, where each δ takes the possible values 0,1. β_q is then the “element for element product” of this masking vector, with the standard coefficient vector β , indicating that the masking vector interacts with the coefficient vector. For example, for two attributes (classes), the parameter vectors would appear $\beta_1=(0,0)$, $\beta_2=(\beta_A,0)$, $\beta_3=(0,\beta_B)$, $\beta_4=(\beta_A,\beta_B)$ ¹. However, it is an important part of the underlying theory of the paper that the class q is not defined by the attribute taking value zero within the class but by the corresponding coefficient taking the value zero. Thus the “random parameters” aspect of the model is a discrete distribution of preference structures across individuals who are distinguished by whether they pay attention to the particular attribute or not.

Since (in our case) the sorting is not observable, we cannot directly construct the likelihood function for estimation of the parameters. In keeping with the latent class approach, we need to estimate a set of probabilities (π_q) that each individual i falls into class q . While this could be conditioned on individual characteristics, in this case we have assumed that the same set applies equally to all respondents, so that the probabilities reflect the class proportions.

Hence the marginal probability that individual i will choose alternative j is found by averaging over the classes, as in (3).

$$\text{Prob}(i,j) = \sum_{q=1}^{2^K} \pi_q \frac{\exp(\beta'_q \mathbf{x}_{i,j})}{\sum_{j=1}^J \exp(\beta'_q \mathbf{x}_{i,j})} \quad \text{where} \quad \sum_{q=1}^{2^K} \pi_q = 1. \quad (3)$$

As formulated, this is a type of finite mixture, or latent class model. It differs from more familiar formulations in that the nonzero elements in β_q are the same across the classes and the classes have specific behavioural meaning, as opposed to merely being groupings defined on the basis of responses as in the strict latent class formulation, hence the reference to a probabilistic decision process model. Estimation of the probabilistic decision process model is straightforward as a latent class MNL model with linear constraints on the coefficients, as suggested above.

3. Empirical application

The data is drawn from a study undertaken in Sydney in 2004 in the context of car driving non-commuters making (stated) 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. More information about the survey is available in Hensher et al. (2005).

A D-optimal design (see Rose and Bliemer 2008, 2009) was used to combine the attribute packages offered to respondents. In addition, the actual attribute levels are pivoted around the knowledge base of travellers. Such designs require explicit incorporation of prior information about the respondents’ preferences into the design. 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.

¹ In this example, there is one unrestricted parameter vector in the model, shown as $\beta_4 = (\beta_A, \beta_B)$. The other parameter vectors are constructed from the same two parameters either by setting one or both elements to zero or by equating elements to those in β_4 . Thus, $\beta_3 = (0, \beta_B)$ is obtained as a linear restriction on β_4 , namely that one element equal zero and a second element equal the corresponding element in β_4 .

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The two SC alternatives are unlabelled routes. The trip attributes associated with each route are summarised in Table 1 together with the variations used for each attribute. These were identified from reviews of the literature and through the effectiveness of previous VTTS studies undertaken by Hensher (2001). All attributes of the SC alternatives are based on the values of the current trip. Variability in travel time, although in the choice scenarios, was found in previous studies not to be statistically significant (in part we suspect due to its specification), and has been excluded in the current model estimation. For all other attributes, the values for the SC alternatives are variations around the values for the current trip.

	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%

Table 1: Trip attributes and profile of the Attribute range in the SC design

The experimental design has one version of 16 choice sets. The design has no dominance given the assumptions that the marginal disutility of all attributes is negative. An example of a stated choice screen is shown as Figure 1.

Figure 1: An example of a stated choice screen

Sydney Road System

Practice Game

Make your choice given the route features presented in this table, thank you.

	Details of Your Recent Trip	Road A	Road B
Time in free-flow traffic (mins)	50	25	40
Time slowed down by other traffic (mins)	10	12	12
Travel time variability (mins)	+/- 10	+/- 12	+/- 9
Running costs	\$ 3.00	\$ 4.20	\$ 1.50
Toll costs	\$ 0.00	\$ 4.80	\$ 5.60

If you make the same trip again, which road would you choose? Current Road Road A Road B

If you could only choose between the 2 new roads, which road would you choose? Road A 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) earlier later

How would you PRIMARILY spend the time that you have saved travelling?

Stay at home Shopping Social-recreational Visiting friends/relatives
 Got to work earlier Education Personal business Other

Back Next

4. Empirical findings

We first estimated an MNL model in which all attributes are assumed to be attended to, and then a probabilistic decision process model with 2^K possible attribute attendance “rules”. However, after extensive inquiry we failed to find a model situation where the toll cost was not attended to, and hence implemented $K=3$ in our empirical application. The final models are summarised in Table 2 including the associated incidence of each non-attendance class. The model that accounts for attribute non-attendance is a significant improvement on the model that assumes all attributes are attended to, in terms of log-likelihood and Bayes information criterion (BIC). Although the probabilistic decision process model has additional parameters, namely the class probabilities π_q , the choice probability part of the model has the same number of parameters as MNL. Mean values of travel time savings (VTTS) are given in Table 2 for the MNL models and the attribute non-attendance model, and are plotted in Figure 2. It is important to note that in those cases where there exist two (non-zero) cost parameters in the class, all VTTS estimates have been calculated using a weighted average cost parameter, with weights defined by the level of each cost attribute; otherwise the single cost parameter is used. When free flow and congested time VTTS are combined, we again use an additional weighting for the trip times associated with each time component.

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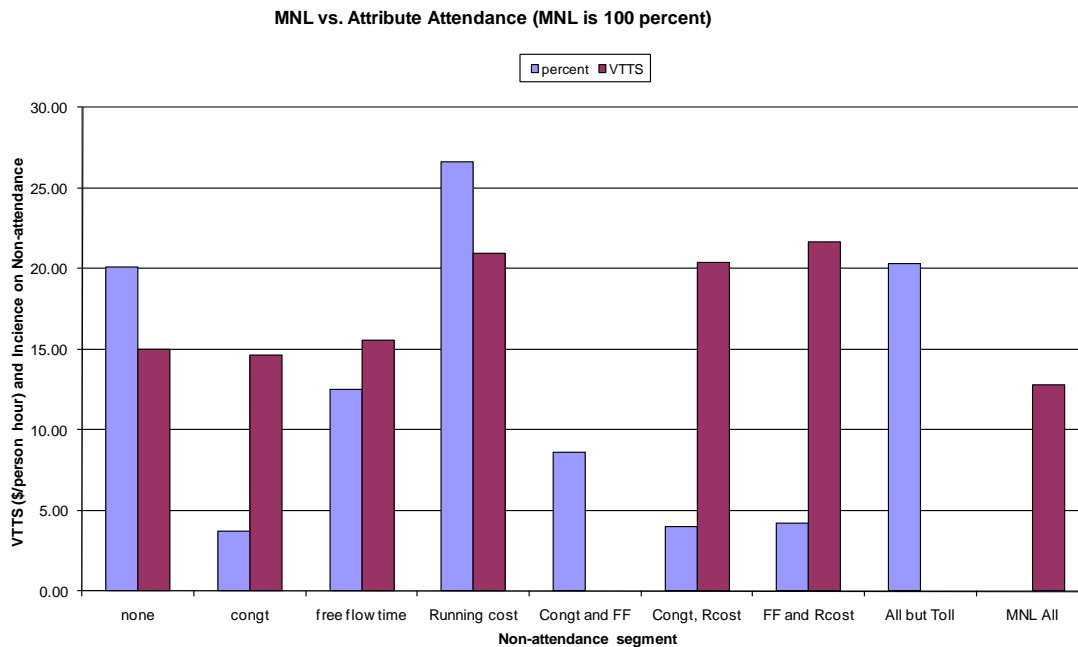
Attributes	MNL	Allowing for Attribute Non-Attendance							
		Attributes not attended to:							
		All attend	Congested time	Free flow time	Running cost	Free flow, congested time	Congested time, Running cost	Free flow, Running cost	Free flow, Congested time, Running cost
Par. (t-ratio)	Par. (t-ratio)	Par. (t-ratio)	Par. (t-ratio)	Par. (t-ratio)	Par. (t-ratio)	Par. (t-ratio)	Par. (t-ratio)	Par. (t-ratio)	
Reference ASC	0.3859 (7.39)	0.4570 (10.57)							
Alternative 2 ASC	0.1328 (2.40)	0.1591 (2.63)							
Free flow time	-0.0682 (-18.96)	-0.1639 (-32.50)	-0.1639 (-32.50)	-	-0.1639 (-32.50)	-	-0.1639 (-32.50)	-	-
Congested time	-0.0847 (-20.05)	-0.1742 (-24.76)	-	-0.1742 (-24.76)	-0.1742 (-24.76)	-	-	-0.1742 (-24.76)	-
Running cost	-0.3079 (-13.86)	-0.8383 (-23.50)	-0.8383 (-23.05)	-0.8383 (-23.05)	-	-0.8383 (-23.05)	-	-	-
Toll cost (Toll)	-0.4069 (-30.86)				-0.4870 (10.57)				
Class membership		0.201	0.037	0.125	0.266	0.086	0.040	0.042	0.203
<i>Model Fit</i>									
BIC	1.5481	1.4376							
Log-likelihood at convergence	-2737.18	-2511.54							
Log-likelihood at zero		-3919.85							
<i>VTTS (\$/person hour) (95% confidence in brackets):</i>									
Free flow time	11.92 (10.33-13.34)	14.40 (11.73-18.92)	14.40 (11.73-18.92)	-	20.52 (17.17-24.78)	-	20.52 (17.17-24.78)	-	-
Congested time	14.82 (12.85-16.59)	15.30 (12.47-20.11)	-	15.30 (12.47-20.11)	21.82 (18.00-26.66)	-	-	21.82 (18.00-26.66)	-
Weighted average VTTS (for free flow and congested time)	13.18 (10-88-15.78)	14.79 (11.81-19.43)	14.40 (11.73-18.92)	15.30 (12.47-20.11)	21.09 (20.57-21.63)	-	20.52 (17.17-27.78)	21.82 (18.00-26.66)	-
<i>Results when classes without both components of travel time are excluded (using re-estimated model with 6 classes):</i>									
<i>VTTS (\$/person hour) (95% confidence in brackets):</i>									
Class membership		0.239	0.0001	0.195	0.276	-	0.061	0.230	-
Free flow time		12.78 (10.30-17.01)	12.78 (10.30-17.01)	-	20.37 (19.30-21.44)	-	20.37 (19.30-21.44)	-	-
Congested time		9.64 (7.77-12.83)	-	9.64 (7.77-12.83)	21.65 (20.76-22.52)	-	-	21.65 (20.76-22.52)	-
Weighted average VTTS (for free flow and congested time)		11.41 (8.40-15.67)	12.78 (10.30-17.01)	9.64 (7.77-12.83)	21.09 (20.57-21.63)	-	20.37 (19.30-21.44)	21.65 (20.76-22.52)	-

Table 2: Summary of models

3,568 observations

The mean VTTS values are in line with the range of estimates that Hensher and colleagues have found in previous studies in Australia in the same tollroad vs. free route context (see, for example, Hensher and Rose 2005 where the mean VTTS \$17.71 per person hour). The highest mean VTTS of \$21.82 per person hour exists where the trading is between the toll and congested time, which is predicted to occur for 4.2 percent of respondents; by contrast, we have the lowest observable VTTS for the situation where the trading is between the free flow time and the two components of cost, although this is only for 3.7 percent of respondents, which seems sensible. In all situations where we allow for attribute non-attendance, the mean estimates of VTTS are much higher than the mean for MNL of \$12.81. The largest class with a mean VTTS of \$20.52 is predicted to contain 26.6 percent of respondents who attend to all attributes except running cost. We can see that 20.3 percent of respondents are predicted to focus only on one attribute, the toll cost, which means that we are unable to calculate a VTTS for this class of respondent. Just over twenty percent of respondents are predicted to attend to all four attributes, and have a mean VTTS of \$15.03.

Figure 2: Value of travel time savings and incidence of non-attendance classes



When we calculate the overall VTTS across the attribute attendance rule classes, weighting each class by the membership probability, we obtain a VTTS of \$12.77 per person hour, compared with the MNL model VTTS of \$13.18 per person hour; but if we were to exclude the two classes where there is no time-cost trade off, we would obtain \$17.96 per person hour. This suggests an under-estimate from the MNL model of mean VTTS by 36 percent. However, this implies that for some respondents (i.e., 28.9%) a VTTS does not exist, which is doubtful. This is a major concern for applications of VTTS, and indeed any WTP study (see Scarpa *et al.* 2009), since we can reasonably assume that everyone does in reality value travel time savings, despite the inability to measure this under certain attribute non-attendance rules.

Nonetheless, it should not be concluded that the MNL model mean VTTS is appropriate, because it delivers an estimate as if all attributes are relevant, which is not an acceptable behavioural rule (Hensher 2006). We are inclined to support the mean VTTS for the subset of decision rules where we can observe a time-cost trade-off (i.e., \$17.96 per person hour), and apply it to the entire population on the argument that the inferred “rules” are behaviourally appealing, despite strictly applying only up to a probability of 0.713.

We believe that this situation has arisen as a result of the design of the stated choice experiment. In particular, the range and levels of specific attributes might be such that some respondents do not see merit in some of the levels of times and costs being traded, with one or both attributes having levels that do not matter². In real markets, it is not unreasonable to suggest that there exist levels of time and cost that do matter, implying that the empirical instrument might not be adequate to pick up the real behavioural response at work. However, there might be some individuals, who would deem a specific attribute not relevant no matter what a sufficiently wide attribute range was considered (e.g., a very wealthy person who does not care about the running cost), and hence never trades-off time with running cost. Furthermore, the situation of a very low level of an attribute might be processed in such a way that relevance only applies when a specific threshold level is reached. This suggests that a more careful assessment of *respondent-specific attribute ranges* is called for in future choice experiment designs.

There could also be other influences at play such as the alternative being chosen for many unknown reasons, so that we have a disproportionately high number of respondents choosing an alternative where either time or cost is not attended to. There is also the serious issue of the design of the stated choice experiment to ensure that the variables presented have meaning and are likely to be of importance in making choices (i.e. relevancy), recognising the behavioural reality of task complexity and possible cognitive burden. Whatever the drivers influencing behavioural response in stated choice studies, be they inherent in the way respondent's think and believe, and/or in inducement from structural elements of the choice experiment, we suggest that attribute non-attendance is a real phenomenon in general.

On balance, we suggest that the real problem is due to the attribute levels associated with each alternative being evaluated, and hence we cannot conclude that a VTTS does not exist. We suspect this finding is not uncommon in choice experiments, but is never known until an analyst undertakes the type of modelling exercise reported in this paper. Scarpa *et al.* 2009 for example, find that over 90 percent of the sample ignore the cost attribute in the context of a stated preference survey designed to value landscapes in Ireland, where the cost attribute was specified as the value in Euros that the respondent would personally have to pay per year through their income tax and value added tax contributions.

We re-estimated the model, omitting the two classes in Table 2 that excluded both time attributes. The VTTS estimates for each class, together with class membership probability, are presented at the bottom of Table 2. The weighted average VTTS is \$16.63 per person hour. The overall fit of this model is -2578.79 which is not as good as the eight class model (-2511.54), with a two-parameter difference (the class membership parameters). Furthermore the relationship between the marginal disutility of free flow and slowed down time (and the associated VTTS estimates) is counterintuitive, with lower mean estimates for slowed down time. This suggests that eliminating two classes that have potential merit, simply because of a data problem that has resulted in 'forcing' trade-offs into a reduced set of attribute non-attendance classes, is itself problematic and questionable.

² Puckett and Hensher (2008) suggest that the range and relative equivalence of the price attribute levels among alternatives in a particular choice task may lead respondents to ignore the price attribute in some choice tasks and not in others.

5. Conclusions

This paper has set out a method to investigate the incidence of all possible combinations of attribute non-attendance for four attributes. The advantage of the approach proposed herein is that there is no need to know the incidence of attribute non-attendance from supplementary questions, given the current concerns about the reliability of such information.

As long as the sample used in model estimation is deemed representative, the evidence on non-attendance of mixtures of attributes can also be used in prediction applications through a simple weighting of the probability outcomes. Hence the approach is valuable beyond the derivation of empirical estimates of willingness to pay.

The biggest challenge for ongoing research is to find a way of accommodating estimates of VTTs where the time-cost trade-offs under specific attribute processing rules are not able to be revealed, a point also highlighted in Scarpa *et al.* (2009). This may require more careful consideration of the relevant set of attributes and a major rethink on how we design choice experiments. We may have been ‘forcing’ behaviourally questionable trade-offs as a consequence of the attribute ranges and levels selected. A way forward might be to identify ranges and levels that are relevant to each sampled respondent (essentially creating thresholds), and use this as priors in the design of SC experiments.

Designs to date, albeit as sophisticated as they are, without exception still define the attribute range based on mixtures of focus groups, pilots and experience by analysts that are not able to truly reflect the range of relevance (i.e., attendance) for each and every sampled respondent. Since the respondents are not known in advance of the main survey, this can only be resolved by some dynamic adjustment built into the experiment at the time of the interview. We have begun investigating this.

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