I T L S

WORKING PAPER

ITLS-WP-08-20

Aggregation of common-metric attributes in preference revelation in choice experiments and implications for willingness to pay

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September 2008

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.

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ABSTRACT: There is a growing literature that promotes the notion of process heterogeneity in the way that individuals evaluate packages of attributes in real or hypothetical markets and make choices. Empirical evidence suggests that individuals use a number of processing strategies such as cancellation, referencing, and attribute aggregation, the latter occurring where there is a common metric. In this paper we consider the threshold relationship between attributes that are defined on a common metric (e.g., minutes or dollars), in order to gain evidence on the extent to which such attributes might be added up or not in preference revelation. The model specification does not require supplementary information on whether specific individuals claimed to have added up attributes; rather we structure a nonlinear utility function that permits a probabilistic preservation or aggregation of each attribute. We translate this new evidence into a willingness to pay (WTP) for travel time savings, and contrast it with the results from the traditional linear additive model, as well as establishing the extent to which self-stated attribute addition systematically varies with WTP and component inputs into WTP. The implications for environmental assessment are highlighted.

KEY WORDS: ***Stated choice designs; information processing; attribute addition; thresholds; willingness to pay***

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DATE: September 2008

1. Introduction

There is a growing literature that promotes the notion of process heterogeneity in the way that individuals evaluate a package of attributes associated with alternatives, in real or hypothetical markets, and in turn make choices (see for example Bonini et al. 2004, Houston and Sherman 1995, Hensher 2006, 2008, Islam et al. 2007, and the more general prospect theory of and Kahneman and Tversky 1979). The recent interest in building process rules into environmental applications is presented in Campbell et al. 2008 and Scarpa et al. 2008. The accumulating empirical evidence suggests that individuals use a number of strategies derived from heuristics to represent the way that information embedded within attributes, defining alternatives, is used to process the context and arrive at a choice outcome. These include cancellation or attribute exclusion, referencing of new or hypothetical attribute packages around a recent or past experience, and aggregation where attributes are in common units (see Gilovich et al. 2002 for a series of papers that synthesise the evidence under the theme of heuristics and biases).

In this paper we explore a line of inquiry in which we consider the threshold relationship between attributes that are defined on a common metric (e.g., minutes or dollars) in order to gain evidence on how such attributes might be processed in preference revelation. We speculate the presence of an underlying continuous probability distribution for the way that pairs of attributes are processed when the units are common. This is consistent with the threshold literature (e.g., Cantillo et al. 2006, Swait 2001).

In the empirical context being studied, this translates into the following behavioural processing strategy: when choosing between a tolled and a non-tolled route as defined by free flow time, slowed down time (or congestion), a toll and running cost of a car, when, for example, the difference between free flow and congestion time is less than a threshold value, the common-metric attributes are added and assigned a common marginal disutility; when the difference is greater than the threshold value, the attributes maintain their own marginal disutility.

Bertini and Wathieu (2006) and Thomas and Morwitz (in press) are recent contributions to a literature on attribute partitioning and numerical cognition that recognizes the role of the structural content of an attribute (in their case it is price) in preference revelation. Price partitioning is shown to act as an incentive to process multiple product dimensions. Although the interest in partitioning is common to our inquiry, our focus is different. We explore ways in which partitioned attributes, such as components of trip travel time (namely free flow time and slowed down or congestion created time), are used to reference particular cognitive experiences which results in the possible redefinition of the marginal (dis)utility of attributes that have a common metric.

The paper is organized as follows. Section 2 proposes a utility specification that captures non-linear attribute processing of common-metric attributes along a continuum from preservation of attribute partition to attribute aggregation. Section 3 describes the empirical context, followed by Section 4 in which the estimated models are presented including willingness to pay measures to value travel time savings, which are contrasted with the evidence obtained under the traditional linear additive model in which common-metric attributes are treated as independent across the entire sample. The paper concludes with a summary of the main findings, including policy implications of the new evidence, and directions for ongoing research.

2. Non-linear processing of common-metric attributes

In this section we develop a utility specification that captures non-linear attribute processing of common-metric attributes over a continuum that accommodates preservation of attribute partitioning and attribute aggregation. Consider a utility function defined in terms of two attributes labelled x_1 and x_2 (these might be free flow time and congestion time, both in common units) and other attributes such as running cost and toll cost x_3 and x_4:

$$U = f\left(x_1, x_2, x_3, x_4\right) + \varepsilon \tag{1}$$

where

$$f\left(x_1, x_2, x_3, x_4\right) = \begin{Bmatrix} \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 & if\left(x_1 - x_2\right)^2 > \alpha \\ \beta_{12}\left(x_1 + x_2\right) + \beta_3 x_3 + \beta_4 x_4 & if \quad \left(x_1 - x_2\right)^2 < \alpha \end{Bmatrix} \tag{2}$$

β_1, β_2, β_3, β_4, β_{12}, are parameters and β_{12} does not necessarily equal a combination of β_1 and β_2. We assume that the standard random utility alternative specific error ε is not dependent on which form of $f(x_1, x_2)$ is operative. The term $(x_1 - x_2)^2$ represents the distance between x_1 and x_2. A squared form is computationally convenient, but another form could be used. Intuitively, when the difference between the common metric attributes x_1 and x_2 is great enough, the agent's process preserves attribute partitioning and thus treats each attribute as separate entities and evaluates their contribution to utility in the standard random utility model manner with parameters β_1 and β_2. On the other hand, when the difference between the common metric attributes x_1 and x_2 is relatively small, the agent's process aggregates the attributes and thus treats the sum of x_1 and x_2 as a single attribute with utility weight β_{12}.

We enrich the model by allowing the α_i for person i to be randomly distributed (with $\alpha_i > 0$). A useful candidate distribution is that α_i is exponential with mean $1/\lambda$ and density $f(\alpha) = \lambda e^{-\lambda \alpha}$. This density has positive mass at zero, and so allows for some fraction of the population to behave exactly as standard optimizers, another set to behave close to standard optimizers with low α_i's, and so they often process the two attributes separately, but there is a tail of others who more frequently are aggregating the two attributes. We assume the α_i's are independent of any other errors in the model. The probability conditions are given in (3). In this model, we assume that there is an exponentially distributed threshold parameter, IID across alternatives and respondents that indicates how the respondent views the attribute components.[1]

[1] At much greater computational cost one might allow for the α_i's to be constant across alternatives for a given respondent. We leave refinements like this for future work.

$$P\left((x_1 - x_2)^2 > \alpha\right) = 1 - \exp^{-\lambda (x_1 - x_2)^2} \tag{3a}$$

and

$$P\left((x_1 - x_2)^2 < \alpha\right) = \exp^{-\lambda (x_1 - x_2)^2} \tag{3b}$$

Integrating over the α_i we write U in conditional form:

$$\begin{aligned} U = {} & f\left(x_1, x_2 \mid \left[(x_1 - x_2)^2 > \alpha\right]\right) P\left(\left[(x_1 - x_2)^2 > \alpha\right]\right) + \\ & f\left(x_1, x_2 \mid \left[(x_1 - x_2)^2 < \alpha\right]\right) P\left(\left[(x_1 - x_2)^2 < \alpha\right]\right) + \varepsilon \end{aligned} \tag{4}$$

Equation (4) implies that:

$$U = (\beta_1 x_1 + \beta_2 x_2)\left(1 - \exp^{-\lambda (x_1 - x_2)^2}\right) + \beta_{12}(x_1 + x_2)\left(\exp^{-\lambda (x_1 - x_2)^2}\right) + \varepsilon \tag{5}$$

Equation (5) is a highly non-linear form in x_1 and x_2. As λ tends toward ∞ the distribution becomes degenerate at zero. In this case, all individuals are always standard optimizers who partition the common metric attributes and we obtain the linear additive form (6).

$$U = (\beta_1 x_1 + \beta_2 x_2) + \varepsilon \tag{6}$$

If λ tends toward 0 then every individual becomes a common metric aggregator, as they perceive no difference between the two attributes. Equation (5) is the estimable utility expression for each alternative in a stated or revealed choice model. In the next sections we set out the empirical context and estimate a multinomial logit (MNL) model, comparing it with the linear additive expression (6).

It is noteworthy that the focus on a (potentially) behaviourally richer specification of the utility expression in a simple MNL model, that recognizes heuristics adopted by choice makers, offers new opportunities to extract greater behavioural richness from simpler econometric specifications, in contrast to preserving the linear additive assumption and introducing random parameters through mixed logit models. In time, we see the research evidence herein being extended to more advanced econometric specifications, but a reappraisal of the linear additive assumption in the context of attribute processing under a simple MNL framework has merit at this stage of gaining a better understanding of the role of processing strategies in conditioning the parameters of specific attributes, and hence willingness to pay for such attributes.

3. Empirical application

The data are drawn from a study undertaken in Sydney in 2004, in the context of car driving 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 stated choice questionnaire presented respondents with sixteen choice situations, each giving a choice between their current (reference) route and two alternative routes with varying trip attributes. The sample of 243 effective interviews, each responding to 16 choice sets, resulted in 3,888 observations for model estimation.

To ensure that we captured a large number of travel circumstances and potential attribute processing rules, we sampled individuals who had recently undertaken trips of various travel times, in locations where toll roads currently exist.[2] To ensure some variety in trip length, three segments were 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 was designed using principles of statistically efficient designs (see Rose and Bliemer 2007, Sandor and Wedel 2002.)[3]; and the behavioural state of the art has moved to promoting designs that are pivoted around the knowledge base of travellers, capturing the accumulated exposure to the studied context (see Rose et al. 2008), in recognition of supporting theories in behavioural and cognitive psychology and economics such as prospect theory, case-based decision theory and minimum-regret theory (Gilovich et al. 2002, Starmer 2000).

A statistically efficient design is a design that minimizes the elements of the asymptotic (co)variance (AVC) matrix, Ω, with the aim of producing greater reliability in the parameter estimates given a fixed number of choice observations. To compare the statistical efficiency of SC experimental designs, a number of alternative approaches have been proposed within the literature (see e.g., Rose and Bliemer 2007). The most commonly used measure is D-error.

$$\text{D-error} = \left(\det \Omega\right)^{1/k} = -\frac{1}{N}\left(\det\left(\frac{\partial LL(\beta)^2}{\partial\beta\partial\beta'}\right)\right)^{-1/k}. \tag{7}$$

where k represents the number of parameters for the design, LL(β) the log-likelihood function of the discrete choice model under consideration, N the sample size, and β the parameters to be estimated from the design. Given that we are generating designs and not estimating parameters for an already existing design, it is necessary to assume a set of priors for the parameter estimates. Given uncertainty as to the actual population parameters, it is typical to draw these priors from Bayesian distributions rather than assume fixed parameter values. Typically normal and uniform Bayesian distributions

[2] Sydney has a growing number of operating toll roads; hence drivers have had a lot of exposure to paying tolls. Indeed, Sydney has the greatest amount of urban kilometres under tolls than any other metropolitan area with the possible exception of Santiago.

[3] The SC experiment herein was designed specifically for the model that was finally estimated from the data. That is, a logit model.

are used (uniform distributions are used if the direction and magnitude of the parameter estimates are unknown; e.g., Kessel et al. 2006)[4].

The two stated choice 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).

Table 1: Trip attributes in stated choice design

Routes A and B
Free flow travel time
Slowed down travel time
Trip travel time variability
Running cost
Toll Cost

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 (games). The design has no dominance given the assumptions that less of all attributes is better.[5] The distinction

[4] The $D_{(b)}$-error is calculated by taking the determinant, with both scaled to take into account the number of parameters to be estimated. It involves a series of multiplications and subtractions over all the elements of the matrix (see for example, Kanninen 2002). As such, the determinant (and by implication, the $D_{(b)}$-error measure) summarizes all the elements of the matrix in a single 'global' value. Thus, whilst attempts to minimize the D-error measure, on average, minimize all the elements within the matrix, it is possible that in doing so, some elements (variances and/or covariances) may in fact become larger. Despite this property, the $D_{(b)}$-error measure has become the most common measure of statistical efficiency within the literature.

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.[6] An example of a stated choice screen is shown as Figure 1 with elicitation questions associated with attribute processing shown in Figure 2.

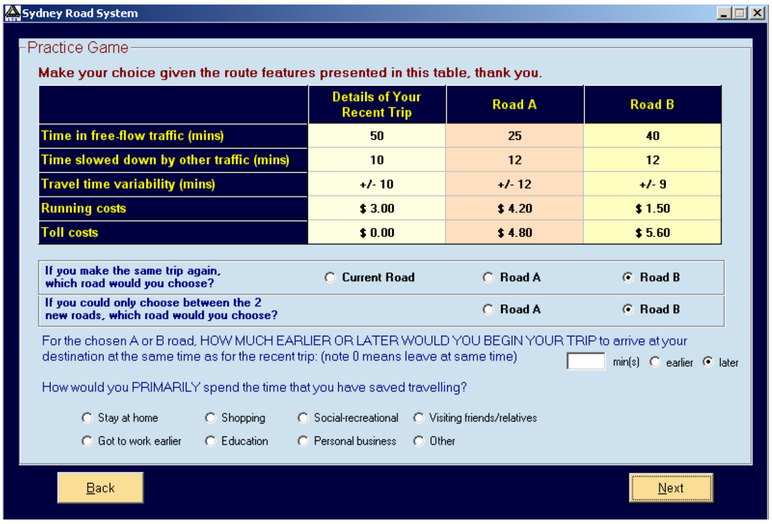

Figure 1: An example of a stated choice screen

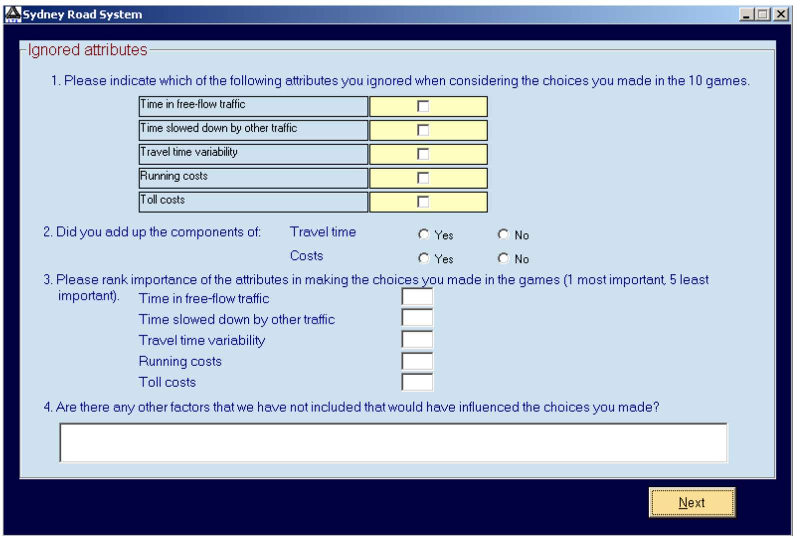

Figure 2: CAPI questions on attribute relevance

[5] The survey designs are available from http://www.itls.usyd.edu.au/about_itls/staff/johnr.asp.

6 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).

4. Empirical analysis

4.1 Model estimates

Two MNL models have been estimated that define the functional hypotheses of interest. The baseline model (Model 1) assumes the common linear additive condition and provides the contrast for the new hypothesis on attribute processing (Model 2). The findings are summarized in Table 3. Model 2 is estimated as multinomial logit using Gauss code[7].

Table 3: Empirical findings for logit process models (t-ratio in brackets). 3,888 observations

	Model 1	Model 2	Attribute
Attributes	Linear Additive	Partition Preservation and Attribute Aggregation	Mean and Standard Deviation
Free flow time (mins)	-0.0686 (-19.33)	-0.0707 (-17.93)	21.51 (13.15)
Slowed down time (mins)	-0.0903 (-30.64)	-0.0916 (-28.54)	30.10 (20.23)
Trip time variability (mins)	-0.0058 (-2.35)	-0.0064 (-2.55)	15.36 (16.08)
Running cost ($)	-0.3136 (-14.89)	-0.3171 (-13.89)	3.32 (1.92)
Toll cost ($)	-0.3613 (-30.36)	-0.3544 (-26.09)	2.81 (2.30)
Combined free flow and slowed down time (mins)	-	-0.0735 (-24.26)	51.62 (22.77)
Combined toll and running cost ($)	-	-0.3676 (-19.75)	6.133 (2.98)
Time Lambda (λ_t)	-	0.7134 (1.19)	
Cost Lambda (λ_c)	-	0.7045 (2.11)	
Non status quo alternative specific dummy (1,0)	-0.2350 (-3.09)	-0.2346 (-3.09)	
Log-likelihood	-3028.83	-3017.19	

The overall goodness of fit improves substantially as we move from the linear additive assumption to the mixed attribute partition preservation and aggregation model. The likelihood ratio test has a test statistic of -23.28 and four degrees of freedom. The p-value is 0.000111, less than the chosen five percent level of significance. Hence we can reject the null hypothesis of no differences. All of the mean parameter estimates have the expected sign and are statistically significant at 95 percent confidence levels or better in Model 1, and nine of the 10 estimates are significant in Model 2. In addition to the time and cost attributes in various forms, we have included a dummy variable to represent the influence of other factors that bias respondent choices towards or away from the reference (or pivot) alternative. This attribute called ‘non-status quo’ has a

[7] Extensive testing using other software (including excel) was used to confirm the parameters in Model 2.

negative sign and indicates, all other factors remaining constant, that there is a bias in favour of the reference alternative.

The two lambda parameters are of special interest because they represent the extent of attribute aggregation versus preservation of attribute partitioning for time and cost. As λ tends toward 0, every individual becomes an "additive" optimizer (i.e., they aggregate the common metric attributes), as they perceive no difference between the two attributes. λ_c is statistically significantly different from zero in excess of 95 percent confidence, whereas λ_t has a t-ratio of 1.19, which is only statistically significant at 77 percent confidence limit on a two-tailed test. On balance, the model supports a mix of attribute aggregation and partition preservation. The particular exponential form is only one such form; we assessed the weibull, however it did not improve on the exponential[8].

4.2 Willingness to pay

We translate this new evidence into a willingness to pay for travel time savings for free flow and slowed down time and contrast it with the results from the traditional linear models. The WTP function for Model 2 is highly nonlinear. The derivative of the utility expression with respect to a specific attribute is given in equation (8), using free flow time (defined as x_1) and in equation (9) using slowed down time (x_2) as examples of the common form. The exact same functional form for equations (8) and (9) applies to running cost and toll cost respectively.

$$\begin{aligned}\partial V / \partial x_1 &= \beta_1 \left(1-\exp^{-\lambda(x_1-x_2)^2}\right) + 2\left(\beta_1 x_1 + \beta_2 x_2\right)\lambda\left(x_1 - x_2\right)\exp^{-\lambda(x_1-x_2)^2} \\ &+\beta_{12}\exp^{-\lambda(x_1-x_2)^2} - 2\beta_{12}\left(x_1+x_2\right)\lambda\left(x_1-x_2\right)\exp^{-\lambda(x_1-x_2)^2}\end{aligned} \tag{8}$$

$$\begin{aligned}\partial V / \partial x_2 &= \beta_2 \left(1-\exp^{-\lambda(x_1-x_2)^2}\right) - 2\left(\beta_1 x_1 + \beta_2 x_2\right)\lambda\left(x_1 - x_2\right)\exp^{-\lambda(x_1-x_2)^2} \\ &+\beta_{12}\exp^{-\lambda(x_1-x_2)^2} + 2\beta_{12}\left(x_1+x_2\right)\lambda\left(x_1-x_2\right)\exp^{-\lambda(x_1-x_2)^2}\end{aligned} \tag{9}$$

To obtain a WTP distribution for each of free flow and slowed down time, we have to either simulate the distribution across values for the attribute(s) of interest or apply the formula to a sample of observations. We chose the latter, using the same data used to estimate the models. Given that the denominator in the WTP expression is a weighted average of the role of running cost and toll cost, where the weights reflect the incidence of running and toll cost, and the numerator includes both attributes with a common metric, the WTP for a specific trip time component (i.e., free flow or slowed down time) is dependent on a mix of levels of all four attributes.

The willingness to pay for travel time savings (VTTS) for each of free flow and slowed down time, after accounting for the utility distributions encapsulating common-metric partition preservation and attribute aggregation, is summarized in Table 4. Model 2 mean estimates are greater than those in Model 1, with an absolute difference of 30

[8] Many functional forms are potentially feasible and might be tested in future, opening a similar path of exploration as occurred in the search for analytical distribution (constrained and unconstrained) for random parameters in mixed logit models.

cents and 22 cents per hour respectively for free flow and slowed down time values, but sizeable variations around these differences given the standard deviations reported for Model 2. This may not seem to be large (respectively 2.42 and 1.35 percent increase), but this translates into substantial differences in time benefits when applied to forecasting toll road benefits, and hence patronage. For example, for toll roads in Sydney, when accounting for the full distribution of VTTS in model 2 for free flow and slowed down time, this translates into an overall time benefit of between \$5m to \$35m per annum depending on which toll road is being assessed.

Table 4: Value of travel time savings ($ per person hour)

	Model 1	Model 2	Model 2			
WTP	Linear Additive	Attribute Aggregation	Quartiles			
Free flow time	$12.42	$12.72 ($5.54)	11.49	12.65	13.17	14.12
Slowed down time	$16.35	$16.57 $5.63)	14.33	16.13	16.94	18.26

Note: weighted average cost parameter for model 1 = -0.33143; model 2 = -0.33006

The non-linear model can be used to derive mean estimates for each quartile across the sampled individuals[9]. The mapping of this is precise to each sampled respondent, unlike random parameter mixed logit models in which the allocation of sampled individuals is random across the distribution[10]. What we have in the quartile findings is recognition of process heterogeneity across the sampled population. Calculating the time benefits for each of the four quartiles, and summing them, gives an estimate of overall time benefits that is different from the evidence based on the comparison between the mean estimate for Model 1 and the full distribution for Model 2. The quartile calculations for a number of toll roads in Sydney result in a time benefit difference that is approximately 96 percent of the estimate based on a comparison of the overall means only. Thus allowing for process heterogeneity at the quartile level (itself a form of aggregation), moves the evidence towards the linear additive model, but only marginally. There are clear gains in recognising the way in which common-metric attributes are processed in preference revelation.

4.3 Willingness to pay and self-stated processing

Given the growing interest in asking supplementary questions to obtain self-stated responses on the processing rule adopted, it is useful to investigate the mapping

[9] We recognise that the linear model with attribute interactions could also be used to obtain attribute-specific distributions, but we have chosen to contrast Model 2 with a strictly linear additive specification given that we have not introduced attribute interactions in Model 2.

[10] Some systematic adjustment can be made by decomposing the random parameter distribution by observed exogenous variables as well as deriving conditional estimated based on knowledge of the chosen alternative (although the allocation is still random within the condition).

relationship between the WTP estimates obtained for each individual and their self-stated responses, in terms of whether they added up the two time attributes and/or the two cost attributes. A large percentage of the respondents stated, in supplementary questions (see Hensher 2008), that they added the components: 88.06 percent and 76.5 percent respectively for time and cost. We regressed the individual specific WTP measures and their constituent components against the two dummy variables representing self-stated time addition and cost addition. The findings in Table 5 suggest that there are some statistically significant systematic variations, with different directional influence across each of the six linear regression models.

Table 5: Mapping value of travel time savings and supplementary questions on process aggregation (N = numerator, D = denominator in VTTS formula based on (8) and (9))

Dependent variable	Constant	Add Time	Add Cost
Value of travel time savings:			
Free flow	12.359 (83.9)	0.6215 (4.0)	-0.2491 (-2.91)
Slowed down time	16.81 (115)	-0.3236 (-2.12)	0.05145 (0.58)
Marginal Disutility of:			
Free flow time (N)	-0.0669 (-82.7)	-0.0032 (-3.66)	-
Slowed down time (N)	-0.0929(-114)	0.0023 (2.64)	-
Running cost (D)	-0.3182 (-206)	-	0.00175 (0.98)
Toll cost (D)	-0.3690 (-243)	-	-0.0037 (2.13)

Note: We also estimated the marginal disutility models including the other addition variable but it did not alter the findings.

Looking at the VTTS, it is interesting to see a statistically significant sign reversal between free flow and slowed down time for the adding of time. All others influences remaining unchanged, we see an updated estimate in VTTS for free flow when attributes are reported as added, and the opposite for slowed down time. For cost addition we have a statistically significant influence for free flow time, however it has a downward impact on VTTS for free flow time when the self-stated response is addition; however the cost addition dummy variable is not statistically significant for slowed down time valuation.

A closer look at the numerator (N) and denominator (D) models highlights some noticeable differences in contribution of the component inputs into VTTS. Adding of cost is not a statistically significant influence on the marginal disutility of running cost, but it is for the toll cost. For toll cost, those who self-state addition tend to have a lower marginal disutility of toll cost, which will increases the overall VTTS, all other influences remaining unchanged. For free flow and slowed down time, the respective marginal disutilities systematically vary according to whether an individual adds up time; however the directional magnitude is more negative for free flow and less negative for slowed down time. It appears that the evidence, on balance, across the sample tends to support increased estimates of VTTS.

Importantly, this evidence does not imply that the self-stated responses are reliable or unreliable, any more than that Model 2 is ‘correct’ or preferred, since the test is nothing more than mapping the evidence between the non-linear model specification, which is a very specific (albeit statistically significant) form, and self-stated responses. The evidence of a sizeable number of statistically significant variables in the six models, however, gives some comfort to the 'reliability' of such self-stated responses.

5. Conclusions

This paper has proposed a new approach to establishing the extent to which an individual preserves the partition of common-metric attributes or adds them up in processing alternatives in choice experiments. Unlike previous studies that have relied on self-stated responses to condition choice outcomes, this paper develops a nonlinear utility specification which permits the data to reveal the extent of preservations and aggregation, up to a probability.

The evidence, albeit from one application, is sufficient proof of concept to claim a case for this common-metric heuristic as one plausible representation of an underlying processing strategy adopted by varying proportions of a population of interest.

The implications on willingness to pay (WTP) for particular attributes suggests that the mean values of travel time savings derived from linear additive MNL models used in the evaluation of toll road projects tend to be downward biased.

The approach has been developed and applied to a strictly defined common metric situation. It has relevance also to what we refer to as closely aligned metrics. For example, where the two 'price' attributes are payment mechanisms of cash and a voucher. The relevance to valuation of environmental attributes such as noise, air quality, accidents, visual amenity and greenhouse gas emissions is self-evident. The studies that have focused on attribute attendance or non-attendance have tended to show reduced mean estimates of WTP when attribute non-attendance is taken into account (although there are exceptions to this directional impact such as Rose et al 2005). In contrast, accounting for the possibility that individuals aggregate common-metric attributes tends to increase the mean estimate. Further empirical studies are required to confirm whether this directional effect is widespread.

Ongoing research (Hensher and Layton 2008) is investigating other common-metric heuristics to establish the extent to which the parameters associate with separate attributes are transferred to other attributes as one way of accommodating cognitive rationalization.

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