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Heterogeneity in decision processes: Embedding extremeness aversion, risk attitude and perceptual conditioning in multiple heuristics choice making

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ABSTRACT:

There is an increasing interest, in the discrete choice modelling literature, in alternative behavioural paradigms that represent ways in which individuals make choices when faced with a choice set of alternatives, under conditions defined by revealed preference, stated choice or a mixture of both data sources. Attribute processing has come of age, and we see many studies using process heuristics such as attribute non-attendance (ANA), relative advantage maximisation (RAM), extremeness aversion (EA) and value learning (VL). With some exceptions (e.g., papers by Hensher, Hess, Scarpa, Campbell and colleagues, and Balbontin et el. 2017, 2017a), the study of each heuristic has been undertaken in isolation from other candidate heuristics; the exceptions being a joint investigation into a fully compensatory model defined by a linear additive in attributes and parameters specification and one process heuristic, commonly using latent class models (reinterpreted as probabilistic decision processing). Within the set of more than one candidate heuristic, limited account has been taken of the possibility that attributes are being processed under varying levels of risk attitude (instead assuming risk neutrality), and where multiple levels of an attribute might be observed in real markets (such as travel time over repeated trips with associated occurrences) and/or designed into stated choice experiments, no account is taken of perceptual conditioning. This paper investigates the role that two behaviourally appealing heuristics or decision rules play jointly in explaining choice making, both of which reflect risk attitude in different ways, where each heuristic contributes up to a probability within a sampled population both within and between respondents' selection of a relevant multiple-heuristic utility expression. We jointly estimate a model that accounts for (i) extremeness aversion and (ii) an extended expected utility transformation for an attribute that accounts for risk attitude and perceptual conditioning. We use a stated choice experiment associated with a commuter car choice between tolled and non-tolled roads in Australia, and compare the key behavioural output, the value of travel time savings (VTTS), obtained from the joint model and two stand-alone models. The findings suggest, after accounting for the probability of choosing each heuristic by each individual, in their construction of an empirical utility expression representing each alternative tolled road, that the mean VTTS from the multiple-heuristic model ($24.32/person hour) lies between the mean estimates obtained from the stand alone models ($21.45/person hour under extremeness aversion, and $29.19 when accounting for risk attitude and perceptual conditioning). The extremeness aversion heuristic has, on average, a 0.63 probability of relevance compared to a 0.27 probability of relevance for the other heuristic. Extremeness aversion (or seeking) is an appealing way of handling degrees of attribute risk that are not explicitly conditioned on the more traditionally identified risk parameter.

KEY WORDS: ***multiple heuristics, risk attitude, perceptual conditioning, extended expected utility theory, extremeness aversion, fully compensatory choices, toll road choices, value of travel time savings***

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1. Introduction

Behavioural economics tells us that choice making increasingly entails a heterogeneous mix of rules or heuristics that individual agents adopt when making choices that are reinforced either through habitual behaviour or which arise from variety seeking behaviour (Dhami 2016). This state of affairs has been represented in the great majority of travel choice studies by freeing up the homogeneity condition attached to parameter estimates, to allow for preference heterogeneity through random parameters, which can be conditioned on systematic sources of influence that narrow down the 'location' of each individual's preferences on the assumed (analytical) distribution of heterogeneity. The mixed logit form is the best example of such a treatment. As we investigate process heuristics, the possibility arises that what is retrieved as taste heterogeneity in standard models may in fact be heterogeneity in decision rules.

For (at least) the last 10 years, a number of transport researchers have questioned the popular underlying assumption of the utility expression as a representation of preference revelation being linear in the parameters and additive in the attributes, allowing also for the inclusion of interaction effects between attributes of alternatives and characteristics of individuals, and/or the context of choice. In the broader literature (notably cognitive psychology, consumer behaviour and decision science), numerous heuristics have been proposed that provide ways of representing preference revelation, with an increasing number being studied and built into research-focussed travel choice models. The linear in the parameters and additive in the attributes model, however, still prevails in the great majority of travel choice models developed for real world applications by government, industry and consultants, including studies that have formed the basis of willingness to pay estimates such as the value of travel time savings in government recommended appraisal guidelines.

Hensher et al. (2015, Ch 21, pp 937-1067)) reviewed the growing array of process heuristics, and Hensher (2014a) focussed on a review of the most popular heuristic, attribute non-attendance (ANA). In an introduction to a special issue of the journal of choice modelling on process heuristics in choice analysis, Hensher (2014) suggested that "…the great majority of choice modelling research has taken, as a maintained assumption, the behavioural position that individuals are fully compensatory in the way that they assess and trade-off attributes in choice making and that in circumstances where the analyst imposes a set of attributes to evaluate, as is common in stated choice experiments, it is commonly assumed that all attributes are relevant in choice making. One consequence of these assumptions is the resulting view that studies that require individuals to assess an increasing number of attributes impose growing complexity and cognitive burden that risks the loss of identifiable comprehendible settings of choice making."

A criticism of this position is that individual choosers are very heterogeneous in the way that they make choices in real and hypothetical markets, and that they draw on rules (or heuristics) to assist them in making choices given the extensive amount of information often available to consider. These rules may vary by contexts typified, for example, by habit or variety seeking behaviour which may be linked in part to accumulated overt experience with certain alternatives (as suggested by Hensher and Ho 2016, and Balbontin et al. 2017). This may also reflect the fact that individuals bring to the choice making setting their views on what attributes are the key drivers of specific choice outcomes, and that these attributes may or may not be included in the set defined by an analyst. There is a real risk that the analyst may self-impose their own views (or prejudices) or even those of a client funding a study, on the number of attributes and alternatives that are deemed comprehendible to a sample of respondents in a survey.

The growing interest in investigating different ways by which individuals might reveal their preferences amongst a set of alternatives has resulted in a long shopping list of candidate rules, many of which are used to simplify decision making, regardless of whether we are studying choices in a revealed or stated choice setting. We see many studies comparing one heuristic against the standard fully compensatory assumption with embedded linear in parameters and additive in attributes (with some amount of interaction between explanatory variables), and a few focussing on a comparison between less commonly tested heuristics in travel choice analysis such as random advantage maximisation (e.g., Leong and Hensher 2014), random regret minimisation (e.g., Hess et al 2012), elimination by aspects (e.g., Hess et al. 2012), and extremeness aversion (e.g., Leong and Hensher 2012).

The literature highlights a view that the behavioural process used in making a choice may vary across respondents within a single sample. Hess et al. (2012), for example, investigated two heuristics at a time in a latent class framework, varying them across four data sets, using mixtures between fully compensatory random utility maximisation models and alternative paradigms, namely lexicography based models, models with multiple reference points, elimination by aspects models, and random regret minimisation models. The modelling approach is tested on three different datasets, where each paradigm-dataset combination reflects the suitability of the data for identifying the decision rule. They find that the behavioural mixing model obtains significant gains in fit and further insights into behavioural patterns. A review of other studies is given in some detail in Hensher et al. (2015) and we will not repeat this, noting however that there remains scope to investigate the way in which one heuristic may work in conjunction with another heuristic (which is not of the standard form) to obtain a renewed understanding of preference revelation, and hence the implications it may have on important behavioural outputs such as willingness to pay estimates.

This paper builds on the contributions by Hensher and his colleagues, especially Stephane Hess, Waiyan Leung, Camila Balbontin, Andrew Collins, Zheng Li and William Greene (see references); but what is different in this paper is the integration through a multiple heuristics specification, within a single utility expression for each alternative, of two particular relatively complex process heuristics. We have selected two behaviourally appealing heuristics to study jointly in explaining choice making, both of which reflect risk attitude in different ways, in a nonlinear additive form, where each heuristic contributes up to a probability within a sampled population selection of a relevant multiple-heuristic utility expression, both within and between respondents. The jointly estimated model accounts for (i) extremeness aversion as one form of risk-accommodating heuristic, and (ii) risk attitude and perceptual conditioning as an extended expected utility attribute transformation (EEUT) (as set out initially in Hensher et al. 2011). This second model form is associated with prospect theory which has been described as the centrepiece of the beginnings of behavioural economics (Dhami 2016).We compare the findings with separate stand-alone models.

The paper is structured as follows. We begin with an overview of the modelling approach, presenting the two heuristics and the way in which they are integrated into a single utility expression. The empirical setting is then presented, with a focus on a stated choice experiment associated with a commuter car choice between tolled and non-tolled roads in Australia. The model findings are presented and interpreted, followed by evidence on a key behavioural output, the value of travel time savings (VTTS), with discussion of the contrast between the VTTS from the joint model and two stand-alone models. The paper concludes with a summary of the main message, and challenges in moving forward in placing process heuristics in the centre of improvements in the behavioural performance of discrete choice models.

2. Modelling Approach

If it is believed that there is heterogeneity in decision processes, i.e., different respondents use different heuristics, one popular approach is to appeal to probabilistic decision process models, which are essentially a form similar to 'latent class' models, but with a twist, where each class has a behaviourally well-defined meaning, and where the functional form of the heuristic under consideration is expressed through the utility expressions in each class (Hensher and Collins, 2011, McNair *et al.*, 2012; Hess *et al.*, 2012, Hess 2012). Typically, each class represents one heuristic, and across the classes, we can establish the role of each heuristic (i.e., class membership), known up to a probability, in establishing an individual's preference for each alternative in a pre-defined choice set.

A suggested alternative to the latent class model form is to probability weight each heuristic directly in the single utility function associated with each alternative in a choice set (e.g., Leong and Hensher 2012, 2012a)[1] and treat the model as a standard logit form such as multinomial or mixed multinomial logit. Within the utility function, this approach allocates the proportional contribution of each heuristic to overall utility, with the possibility of linking the share outcome to the characteristics of respondents and other possible contextual influences. In a model with a total of M heuristics, the weights of each heuristic, denoted by HW_m, $m=1,2,\ldots,M$ can be given by means of a logistic function shown in equation (1).

$$HW_m = \frac{\exp(U_m)}{\sum_{m=1}^{M} \exp(U_m)} \qquad (1)$$

The weight can be directly calculated from the contribution of each heuristic to the utility of an alternative using this logit form to capture the role of each heuristic within the overall logit model of the choice model, i.e. for two heuristics we have $U_j = HW_{H1} * U_{H1} + HW_{H2} * U_2 + \varepsilon_j$. We now discuss the two heuristics of special interest. Estimation of this model requires a non- linear logit form (see Chapter 20 of Hensher et al. 2015).

2.1 Heuristic 1: Extremeness Aversion

The first heuristic arises from the Kivetz *et al.* (2004) specification for the extremeness aversion heuristic. The modelling approach uses the contextual concavity specification of equation (2), where the context dependence stems from the part-utilities of each attribute in the utility function being expressed as gains relative to the minimum part-utility of the same attribute in that choice set.

If the notion of diminishing returns in the contextual concavity model is accepted, the prior expectation is for φ_k to satisfy the inequality $0 < \varphi_k < 1$, $k=t,c$. In the model, we allow φ_k to be freely estimated, and have chosen a form where the reference (i.e., "worst") attribute level, defined as the maximum of each of the time and cost components in the choice set, precedes the minus sign; hence the prior expectation is for $\hat{\beta}_k$ to be positive. The functional form for this heuristic (as a contextual concavity model) is given in equation (2) which summarises the utility expression for each unlabelled alternative in a choice set used in the empirical application.

[1] Recent research by Balbontin, Hensher and Collins (2016) has suggested the potential equivalence, empirically, between the latent class approach and the multiple heuristics approach used in the current paper.

$$\begin{aligned}
&\mathrm{U(current)} = \mathrm{RefASC}\ +\left(\beta_t * (\mathrm{time}_{\max} - \mathrm{time})\right)^{\varphi_t} + \left(\beta_c * (\mathrm{cost}_{\max} - \mathrm{cost})\right)^{\varphi_c} + \varepsilon_0 \\
&\mathrm{U(alt1)} = \left(\beta_t * (\mathrm{time}_{\max} - \mathrm{time})\right)^{\varphi_t} + \left(\beta_c * (\mathrm{cost}_{\max} - \mathrm{cost})\right)^{\varphi_c} + \varepsilon_1 \\
&\mathrm{U(alt2)} = \left(\beta_t * (\mathrm{time}_{\max} - \mathrm{time})\right)^{\varphi_t} + \left(\beta_c * (\mathrm{cost}_{\max} - \mathrm{cost})\right)^{\varphi_c} + \varepsilon_2
\end{aligned} \tag{2}$$

With the exception of the reference alternative specific constant (RefASC), all other parameters are treated as generic across alternatives, given the unlabelled choice experiment used in this paper.

2.2 Heuristic 2: Extended Expected Utility Attribute form with Risk Attitude and Perceptual Conditioned Travel Time

Allais (1953) in his paradox suggests that *designed* probabilities associated with attribute level occurrence over repeated use or consumption, given in a few applied travel choice experiments (e.g., travel times experienced over a number of regular daily commuting trips as in the current data set) are in reality transformed by respondents. A series of probability weighting functions have been introduced in a number of travel choice studies to account for this perceptual transformation of probabilities in experiments (referred to as perceptual conditioning or decision weights). One form, proposed by Prelec (1998), is $w(P) = \exp(-(-\ln P)^{\gamma})$, where *w(P)* is a non-linear probability weighting function, which converts raw probabilities (*P*) associated with attribute $x_1, x_2, \ldots x_R$ with R levels over R occurrences, as shown typically in a stated choice experiment (see below). We can write out the full utility expression as equation (3) which also includes a risk attitude parameter, α. We have adopted the popular constant relative risk aversion (CRRA) specification for analysing the attitude towards risk (see Holt 2002), which postulates a power specification (e.g.,$U = x^{\alpha}$). There are a number of other variables (S) in the utility expression that are not specified this way, and are typically added in as linear in parameters. The presence of α and γ in equations (3) and (4) results in an embedded attribute-specific treatment in the overall utility expression associated with each alternative that is non-linear in a number of parameters, which we call the extended expected utility transformation (EEUT) (Hensher et al. 2011) because it extends the expected utility theoretic model to accommodate one contribution of prospect theory through the decision weights. Only if $(1-\alpha)$ = 1, and γ=1 does equation (3) collapse to a linear utility function.

Under a concave utility function (α >0), this implies a risk-averse attitude, i.e., a sure alternative is preferred to a risky alternative (i.e., with multiple possible outcomes) of equal expected value. A convex utility function (α <0) suggests risk taking, i.e., a risky alternative is preferred to a sure alternative of equal expected value. A linear utility function (α =0) indicates risk neutrality, i.e., a risky alternative is indifferent to a sure alternative of equal expected value.

$$EEUT(U) = \beta_x \{[W(P_1)x_1^{1-\alpha} + W(P_2)x_2^{1-\alpha} + \ldots + W(P_R)x_R^{1-\alpha}]\} \tag{3}$$

$$U = EEUT(U) + \sum_{z=1}^{Z} \beta_z S_z \tag{4}$$

3. Empirical Setting

The dataset used in this paper is obtained from a stated choice study undertaken in 2008 on a proposed toll road in Australia. The experimental design consisted of 32 choice situations, with each of the 752 respondents given a block of 16 choice situations. Each choice situation consisted of the current trip as well as two unlabelled hypothetical experimental alternatives, with the levels of each attribute of the hypothetical alternatives pivoted around the level of the corresponding attribute in the current trip. The exception is the toll cost attribute.

As most respondents reported not having to pay a toll in their current trip, the levels of the toll cost attribute are fixed over a range from no toll to $4.20, with the upper limit determined by the trip length of the respondents reported trip. Figure 1 illustrates the choice task presented to the respondents. The experiment was designed according to the D-efficiency criterion, which increases the statistical efficiency of the model for a given sample size, compared to less statistically efficient methods such as orthogonal designs (Hensher et al. 2015, Rose and Bliemer, 2008). Full details of the design of choice experiment are detailed in a number of other readily accessible papers (e.g., Hensher et al 2011, Hensher and Li 2012, and Li and Hensher 2015).

Figure 1 Screen capture of illustrative choice task

Given the paper is focussed on the role of heuristics in choice experiments, for extremeness aversion we will focus only on the aggregate time and cost of the trip (see Leong and Hensher (2012) for a disaggregation of time and cost under EA only) in model estimation, whilst for the risk attitude heuristic we also account for the probability of early, on-time and late arrivals. For the modelling purposes at hand, the socioeconomic profile of the data is given in Table 1, while the attributes of the choice tasks are summarised in Table 2.

Table 1 Descriptive Statistics of Selected Socioeconomic Characteristics

Statistic	Mean	Std Deviation
Gender (female=1)	0.575	0.496
Income ($)	57,892	37,689
Age (years)	39.44	13.01

Table 2 Descriptive Statistics for Modelled Attributes

Attribute	Mean	Std Deviation
Arrive on time (minutes)	39.28	16.58
Arrive early travel time (mins)	34.48	14.97
Arrive late travel time (mins)	48.89	21.09
Running and toll costs ($)	4.56	3.02
Maximum travel time (mins)	44.32	17.59
Maximum travel cost ($)	6.34	2.99
Proportion choosing current (reference alternative)	0.696	
How many times the recent trip route is used a year	19.08	10.39

4. Results

The findings from three non-linear logit models are summarised in Table 3[2]. The overall statistical fit of all models is similar; however, using the AIC criterion, which allows for differences in degrees of freedom, we find that the two-heuristic model is the preferred form to represent preferences of the sampled respondents. All of the estimated parameter estimates are statistically significant and of a behaviourally meaningful sign. Surprisingly, we were not able to identify any statistically significant stand-alone socioeconomic influences, but with personal income improving the statistical performance of cost as an interaction term in the second heuristic. The mean α estimate is 0.4746, hence 1 minus α is smaller than unity, suggesting a risk averse attitude. There is presence of clear perceptual conditioning associated with the levels of travel time and their probabilistic occurrence in repeated commutes. Figure 2 suggests that we have over-prediction at low probabilities of occurrence up to around 0.35, and under-prediction above 0.35. The deviations are very stark, with the greatest deviations at around 0.2 and 0.7.

Of particular interest is the contribution that each heuristic makes to the overall utility expression, defined in terms of the probability of contribution to overall utility associated with an alternative. The distribution across the sample is given in Figure 3, where we have a mean of 0.632 (standard deviation of 0.133) for the extremeness aversion heuristic, and 0.273 (standard deviation of 0.132) for the risk and perceptual conditioning EEUT heuristic. The range varies substantially from 0.455 to 0.905 for EA, and from zero to 0.450 for the EEUT heuristic, with very little overlap in the overall sample.

[2] We estimated a number of random parameter models but could not find a model that obtained the statistically significant parameter estimates we have obtained in the selected models.

Table 3 Model Estimation Results

Attribute	Joint Heuristics	Extremeness Aversion (EA)	EEUT Risk Attitude and Perceptual Conditioning (RA_PC)
RA_PC:			
Total cost*income ($)	-2.44725 (-2.25)		-0.2641 (-15.06)
Gamma (PC) (γ)	4.5155 (1.97)		0.3065 (5.62)
Alpha (PC) (α)	0.4746 (2.94)		0.1213 (2.17)
Expected time (mins)	-0.4773 (-3.74)		-0.214 (-1.98)
Reference alternative constant	0.7533 (13.22)	0.5653 (7.22)	0.6270 (7.99)
EA:			
Max time-time	0.0652 (7.24)	0.0703 (16.62)	
Max cost-cost	0.2733 (2.65)	0.3404 (10.21)	
Contextual concavity cost (φ_c)	0.5118 (4.34)	0.6533 (8.38)	
Contextual concavity time (φt)	1.6793 (8.73)	0.9794 (11.21)	
Heteroscedastic conditioning:			
Number of times recent trip is undertaken per annum	0.0220 (4.66)	0.0172 (5.33)	
Log likelihood at zero	-4921.78		
Log-likelihood at convergence	-3381.18	-3419.54	-3450.62
AIC/sample size	1.514	1.529	1.543
McFadden pseudo R^2	0.313	0.305	0.299

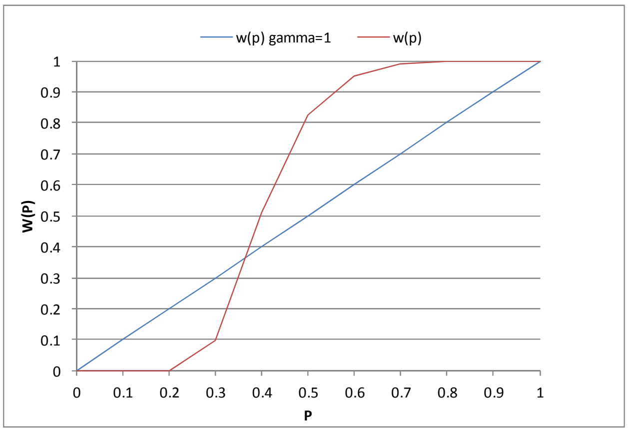

Figure 2 Non-linear probability weighting function in the joint heuristic model

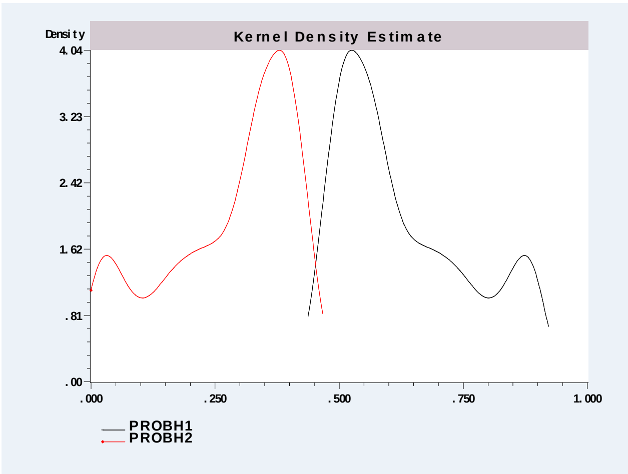

Figure 3 Distribution of probability of heuristics contribution to overall utility of an alternative

The results obtained from the joint model and the stand alone EA model show that all the $\hat{\varphi}$s and $\hat{\beta}$s are statistically significant at the five percent level (and many at the one percent level), with the $\hat{\beta}$s possessing the correct signs. Relative to the stand alone EA model, results from the likelihood ratio test suggest that embedding a contextual heuristic into the joint model provides a better overall statistical fit at the 1% level of significance; given a likelihood ratio of 76.72, which is greater with five degrees of freedom than the $\chi^2_{(5)}$ value of 15.01 at 0.01 level of significance.

Concavity of the power parameter can be tested by comparing the null hypothesis $H_0 : \hat{\varphi} = 1$ (no concavity, i.e., linear in the attributes) against the alternative hypothesis $H_1 : \hat{\varphi} < 1$ (concavity). We can reject the null hypothesis $\hat{\varphi}_c = 1$ for cost, in favour of the alternative hypothesis $\hat{\varphi}_c < 1$ (=0.5118), at the five percent significance level. This finding is consistent with a concavity power parameter. With all else equal, respondents are extremeness averse when evaluating the cost attribute.

For travel time, we have a rejection of the null hypothesis $\hat{\varphi}_t = 1$ in favour of the alternative hypothesis $\hat{\varphi}_t > 1$ (=1.6793), leading us to the conclusion that respondents are treating utility gains in travel time as a convex function, rather than a concave function. Instead of an extremeness aversion heuristic, we now have empirical evidence supporting an extremeness seeking heuristic being used to evaluate the travel time component. However, full extremeness seeking in the sense of Gourville and Soman (2007) requires all the power parameters to be greater than one. When extremeness aversion is not exhibited in all attributes of the alternatives, it may be concluded that respondents in this choice context are exhibiting the polarisation effect.

Relative to the stand alone EEUT model with risk attitude and decisions weights, results from the likelihood ratio test suggest that embedding this EEUT model heuristic into the joint model provides a better statistical fit at the 1% level giving a likelihood ratio of 138.9, which is greater with five degrees of freedom than the $\chi^2_{(5)}$ value of 15.01 at 0.01 level of significance. We now turn to the willingness to pay estimates for travel time savings.

5. The Value of Travel Time Savings

A main focus of this research is to establish if there are differences between the value of travel time savings (VTTS) obtained from the joint models and the two stand-alone models.

$$VTTS = 60 * \frac{\partial V}{\partial T} / \frac{\partial V}{\partial C} \tag{5}$$

For extremeness aversion, the marginal disutility expressions for travel time and travel cost are given as equations (6) and (7).

$$\frac{\partial V}{\partial T} = -\beta_t^{\varphi_k} \varphi_t (\mathrm{T}_{\max} - T_j)^{\varphi_t - 1} \tag{6}$$

$$\frac{\partial V}{\partial C} = -\beta_c^{\varphi_c} \varphi_c (\mathrm{C}_{\max} - C_j)^{\varphi_c - 1} \tag{7}$$

The marginal disutility expressions for travel time and travel cost, in which travel time is conditioned on risk attitude and decision weights under EEUT, are given as equations (8) and (9).

$$\frac{\partial V}{\partial T_k} = \sum_{k=1}^{3} [\exp(-(\log(\mathrm{ProbT}_k))^{\gamma})] * [-\beta_t (1-\alpha)(\mathrm{T}_k)^{(1-\alpha)}] \tag{8}$$

where k=1 (early), 2, (on time), and 3 (late).

$$\frac{\partial V}{\partial C} = -100\beta_v / income \tag{9}$$

The findings, given in Table 4, suggest, after accounting for the probability of choosing each heuristic by each individual in their construction of an empirical utility expression representing each alternative tolled road, that the mean VTTS from the multiple-heuristic model is $24.32/person hour, while the mean estimates obtained from the stand alone models are $21.45/person hour under extremeness aversion for cost and extremeness seeking for time, and $29.19 when accounting for risk attitude and perceptual conditioning under EEUT[3]. The mean VTTS from the two-heuristics model is probability weighted to account for the role of each heuristic in defining preferences and then summed. It is encouraging to see that the joint model VTTS lies between the mean estimates obtained from the stand alone models. The distributions of VTTS for each of the three models are summarised in Figures 4 and 5.

The extremeness aversion (seeking) heuristic has, on average, a 0.63 probability of relevance compared to a 0.27 probability of relevance for the EEUT heuristic. The extremeness aversion (seeking) is also a way of handling degrees of attribute risk that are not explicitly conditioned on an identified risk parameter. Since the risk attitude parameter is associated only with the travel time attribute in heuristic 2, and in heuristic 1 travel time exhibits extremeness seeking, it is interesting to speculate as to whether we are picking up, in the joint model, two dimensions of risky behaviour, each applicable up to a probability. Heuristic 2 is reflecting on travel time reliability within an alternative, whereas heuristic 1 is accounting for the differences in a single travel time offered amongst the alternatives. What is also of coincidental interest is the somewhat lower mean estimate ($6.28) for the heuristic on risk attitude and perceptual conditioning under EEUT, which is similar to the $7.73 per person hour mean estimate, also under EEUT, found in Hensher et al. (2011) using the same data, but with random parameters for α, γ, expected time and cost parameters. Does this suggest that the comment made in the introduction that the possibility arises that what is retrieved as taste heterogeneity in standard models may in fact be heterogeneity in decision rules may have some merit?

Table 4 Values of Travel Time Savings ($2008 per person hour).

Standard deviation estimates are in brackets

	Joint Heuristics	Extremeness Aversion (seeking) (EA(S))	EEUT Risk Attitude and Perceptual Conditioning (RA_PC)
	24.32 (9.17)	21.45 (2.75)	29.20 (1.59)
EA(S) (H1)	18.03 (9.16)		
RA_PC (H2)	6.28 (4.46)		

[3] A simple multinomial logit model, linear in parameters and additive in attributes, gives a mean VTTS of $14.32/person hour. The mean estimate with random parameters (with an unconstrained normal distribution) for time and cost is $7.57/person hour.

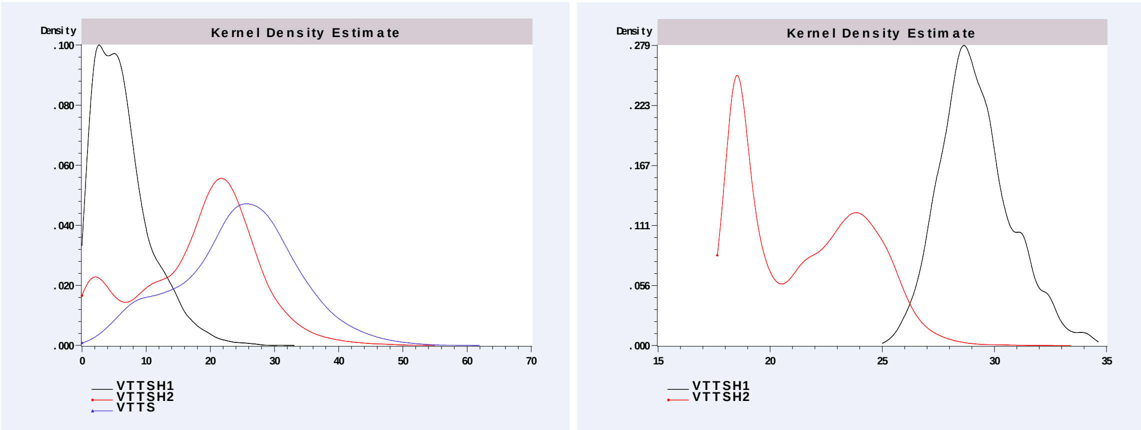

Figure 4 Kernel distribution of VTTS across the sample: (a) joint model (b) stand-alone models

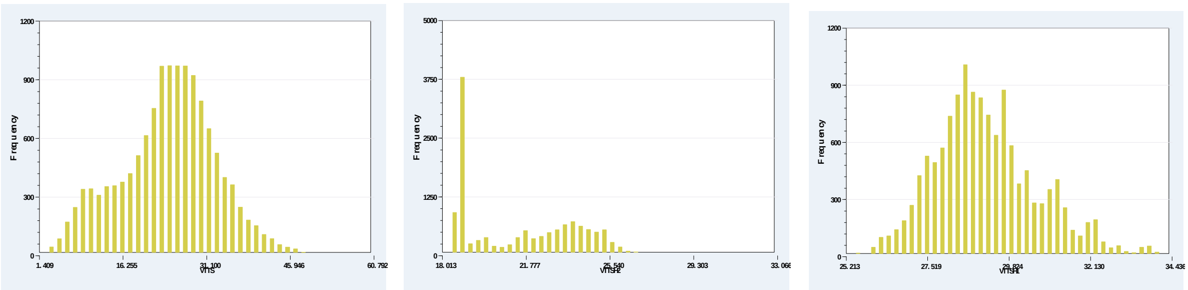

Figure 5 Histograms of the distribution of VTTS across the sample from left to right are (a) joint model (b) ES (s) model and (c) EEUT RA_PC model

6. Conclusions

This paper contributes to a small but growing literature on embedding multiple decision process heuristics into discrete choice models, as a way of improving the representation of the way that heterogeneous individuals make choices. We have chosen two specific heuristics, both of which have been shown in the wider literature to be appealing ways of representing preference revelation in choice making. This is the first study, to our knowledge, that has included risk attitude and perceptual condition within EEUT in a multiple heuristic travel choice framework[4].

We did investigate the inclusion of three and four heuristics, with the addition of a linear additive specification and a random advantage maximisation (RAM); however we were unable to find a model form that delivered statistically meaningful evidence across all embedded heuristics. There was one exception, when we included a linear in parameters and additive in attributes model (the usual one commonly estimated); however all parameter estimates associated with this fully compensatory standard heuristic were not statistically significant, and impacted in a way that affected the statistical performance of parameters associated with the other two heuristics. This might explain why other

[4] Harrison et al. (2014) discuss decision rules in a dual decision approach which explicitly employs multiple criteria for the evaluation of prospects. They also review the broader literature in psychology and economics.

studies (e.g., Hess et al. 2012) have only investigated two heuristics in a model. What this suggests is that there is the possibility of a high likelihood of confoundment (or serious correlation) between specific heuristics, and that future research using simulated data might be useful in investigating this suggestion.

The empirical evidence on the role of risk attitude and perceptual conditioning associated with part of the utility expression as EEUT, that is defined up to a probability, is an important finding, and its inclusion with a heuristic on extremeness aversion (or seeking), suggests that risk can be treated in various ways given that the contextual concavity (or convexity) model is also picking up some element of risky choice making (in a different way) in the sense that the individual is looking to choose that alternative which is as 'far away' in preference space from the worst case scenario on offer, in order to reduce the risk of making a choice that they regret (suggesting also that this may have some elements that are similar in purpose to random regret). The chosen heuristics appear to be a behaviourally very appealing mixing of decision rules which each act up to a probability in revealing preference heterogeneity within a sampled population.

The findings on the value of travel time savings are especially interesting, since they show very convincingly that individual heuristics tend to provide estimates of VTTS that are either (on average) too high or too low *if in fact* the choices made are the product of a mixed processing strategy in a population, but not in the sense that one heuristic applies fully to an individual, but rather in the sense that more than one decision heuristic is used up to a probability to reveal preference heterogeneity across a sampled population that is now deepened within the representation of each individual's preferences in choice making.

While some might see this as added complexity in modelling, it is becoming increasingly evident, in many studies, that we can no longer just take, without question, the default simple linear in parameters and additive in attributes approach (even if it is enhanced with linear interactions and random parameters) as behaviourally relevant. We must continue to find ways to embed more realistic processing heuristics in ways that will, in time, make it easy and become standard practice in real world applications.

The real prospect that we might, in time, be able to replace the popular random parameter form, which continues to remain controversial in respect of the choice of analytical distributions, as a way of capturing preference heterogeneity, with fixed parameter models that are enlightened by a mixture of process decision rules, is very encouraging. This seems to be a potentially more behaviourally appealing way of capturing notable preference heterogeneity (see Balbontin et al. 2017a). The evidence in this paper aligns well with suggestions made in Hensher et al. (2013, page 1017) that:

"… a random parameter treatment … may be confounding with attribute processing; and that including attribute processing in the absence of continuously distributed random parameters is preferred to including continuously distributed random parameters in the absence of attribute processing. This is an important finding that might suggest the role that attribute processing rules play in accommodating attribute heterogeneity, and that random parameters within class are essentially a potential confounding effect."

7. References

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