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Consistently inconsistent: The role of certainty, acceptability and scale in automobile choice.

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TITLE: **Consistently inconsistent: The role of certainty, acceptability and scale in automobile choice.**

ABSTRACT: The way in which respondents behave in stated preference experiments is of interest to many practitioners in the field of choice modelling. This paper draws together three increasingly prevalent concepts in the literature; the role of scale; choice certainty calibration as a method for reducing hypothetical bias; and the acceptability of alternatives as a method for better representing respondent choice behaviour. Using a scaled multinomial logit model to focus on the role of scale, it is found that the amount of idiosyncratic error in the context of automobile is significant. Choice task certainty is found to be a function of several respondent characteristics and can be used to decompose scale. In doing so, it is found that for choice tasks where there is less certainty about the choices made, the scale parameter is lower and hence these choices are more stochastic, particularly in the case of reduced alternatives. In comparing different approaches to incorporating certainty, it is found that parameter estimates differ substantially depending on what method is employed. The implications of a lack of a theoretical framework with respect to choice certainty are discussed, as are the implications of removing unacceptable alternatives from the modelling process.

KEY WORDS: ***Scale; heterogeneity, certainty; vehicle choice; preferences; scaled multinomial logit; choice survey; respondent behaviour; acceptability.***

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1. Introduction

A key assumption underlying random utility theory, from which most discrete choice models are derived, is that respondents are rational economic agents who are able to consistently reveal their preferences by choosing from a variety of alternatives after trading one attribute of the product with another. However, when presented with similar, if not identical choice tasks, an individual respondent will often behave in a heterogeneous manner in terms of the choices they are observed to make. Failure to acknowledge this heterogeneity in the modelling processes may induce biases in subsequent measures such as willingness to pay or elasticity estimates. While several modelling solutions to this problem are available, many of these techniques assume that any heterogeneity that is observed is a result of the differences in preferences exhibited between each respondent.

It is equally possible however that any differences in observed choices may also arise because the behaviour of each respondent over repeated choice tasks is inconsistent. Sources of this inconsistency are likely to be varied. Respondents may be more or less consistent in the choices they are observed to make for some alternatives than they are for others due to differences in experiences, attitudes, perceptions, or some other unidentified construct held by the population for the various alternatives under consideration. Alternatively, respondents may be more or less consistent in the choices that they make irrespective of the alternatives on offer due, for example, to general laziness, inattention to the choice task, or differences in overall cognitive ability.

This source of difference is commonly referred to as scale heterogeneity (Fiebig et al. 2010) and represents the amount of idiosyncratic error in the responses provided by each respondent. A review of the literature suggests that homogeneity of preferences in choice processes may be more common than previously thought and that potentially much more of the preference heterogeneity observed in attributable to inter-personal differences in the scale (Louviere et al. 1999, Swait and Bernardino 2000, Louviere and Eagle 2006, Louviere and Meyer 2008, Fiebig et al. 2010, Salisbury and Feinberg 2010). Evidence has been presented that the complexity of a choice task, defined in terms of the number of alternatives, number of attributes and the range of the attribute levels, can impact upon the level of scale, and thus lead to less deterministic choices (Swait and Adamowicz 2001, Hensher 2006, and Rose et al. 2009). These results suggest that increased attention should be paid to factors that may influence the presence and amount of scale that exist in a given data set.

In the completion of stated preference tasks, it has been shown that respondents adapt their decision strategies to the context in which the decision is being made, with the amount of effort required dependent upon the benefit of making a good choice (Payne et al. 1992, 1993). Similarly, it is hypothesised that if respondents are more (less) engaged by the choice task they are completing, they are induced to provide greater (lesser) effort and thus more consistent (inconsistent) choices (Bonsall et al. 2007), and that experience with the subject of the choice task itself can also lead to improvement in choice consistency (Scarpa et al. 2003 and Feit 2009). There is also evidence that the number of individuals involved in a decision effect scale heterogeneity, with evidence suggesting that when groups are involved in the choice process the input from the additional agents engenders additional heterogeneity (Hensher et al., *Forthcoming*).

One way of potentially determining the degree of confidence a respondent has in the choices they make, and thus potential consistency of responses, is to use a certainty index. Originating from research on hypothetical bias within the contingent valuation literature (the degree to which results from typically hypothetical studies deviate from real market evidence) a certainty index is one method used to calibrate hypothetical choices such that the effects of hypothetical bias can be mitigated. There are two different response mechanisms commonly employed for capturing choice certainty within stated preference experiments; a follow up question asking respondents to assess their level of certainty on a scale of some description such as one to ten or zero percent to 100 percent; or asking respondents to qualitatively evaluate their level of certainty using categories such as "probably sure" or "definitely sure". In using such scales, typically respondents are asked to evaluate the level of certainty they have about the choice they have just made, and by using a threshold level of certainty willingness to pay estimates, are recalibrated accordingly. Such a technique has proven to be useful in eliminating potential bias induced by the hypothetical nature of an experiment (Champ et al. 1997, Johannesson et al. 1999 and Blumenschein et al. 2008).

Such methodology is now being employed within the stated choice literature (Bailey 2005, Ready et al. 2010 and Swardh 2010), whereby certainty is measured on a scale, and models subsequently recalibrated on choices where some certainty threshold was obtained. Rather than eliminate choice tasks where reported certainty failed to meet a prescribed level however, an alternative approach that is sometime employed involves using the certainty index to probability weight choice tasks, and hence placing greater emphasis on choice tasks with higher degrees of certainty in the estimation procedure. An alternative way to conceptualise this certainty index is as an expression of the degree of error the respondent is reporting in their response, the assumption being that the more uncertain a respondent is the choices they are making the more inconsistent their choices will be. Thus another approach to introducing the concept of certainty into the examination of stated preference data is via the scale parameter.

Within the literature, examination of scale as a function of certainty is very limited. Brouwer et al. (2010) examine changes in scale as a function of increased familiarity with the choice task, and whilst they find strong indications that preference precision increases over the choice task (i.e., reductions in scale are observed), the differences in relative scale parameters cannot be proven to be statistically significant. However, analysing changes in reported certainty independent of scale, the authors do find significant increases in choice certainty as the respondent completes more choice tasks, indicating a learning and/or experience effect. However, because changes in scale and certainty are measured independently, it is unclear as to what role uncertainty may play in increasing the amount of respondent specific error within a choice task. The authors also restrict their examination of scale differences as a function of the number of choice tasks completed, when in fact scale (or response inconsistency) may occur at any point within the choice task.

The objectives of this paper are threefold; firstly to examine the level of certainty reported by respondents in the context of automobile choice, identifying any systematic factors that attribute to a greater or lesser degree of certainty in the choices made; secondly to examine the effect of scale, and to assess the role of choice task certainty across all choice tasks in decomposing the effect of scale; and thirdly, compare and contrast the different ways in which certainty may be used to calibrate stated preference models. The paper is structured as follows. In the next section an overview of the generalised mixed logit model is given. Section 3 provides a review of the stated preference survey used in collecting the data for this study. Section 4 describes the general characteristics of the data under analysis and discusses the results of the empirical modelling. Finally, Section 5 provides discussion and concluding remarks, highlighting directions of future research.

2. Methodology

Let U_{nsj} denote the utility of alternative *j* perceived by respondent *n* in choice situation *s*. U_{nsj} may be partitioned into two separate components, an observed component of utility, V_{nsj} and a residual unobserved (and un-modelled) component, ε_{nsj}, such that

$$U_{nsj} = V_{nsj} + \varepsilon_{nsj}. \quad (1)$$

The observed component of utility typically requires the estimation of coefficients, δ, linked to the observed attribute levels, *x*, of each alternative *j* such that

$$U_{nsj} = \delta_n x_{nsj} + \varepsilon_{nsj}, \quad (2)$$

where δ_n represents a vector of coefficients associated with the attributes observed by respondent *n* and the unobserved component, ε_{nsj}, is assumed to be independently and identically (IID) extreme value type 1 (EV1) distributed. Under this notation, δ_n can assume any distribution, and hence approximate any random utility model (see McFadden and Train 2000). As well as containing information on the levels of the attributes, *x* may also contain up to *J*-1 alternative specific constants (ASCs) capturing the residual mean influences of the unobserved effects on choice associated with their respective alternatives; where *x* takes the value 1 for the alternative under consideration or zero otherwise.

It is possible to re-parameterise the coefficients δ_n such that $\delta_n = \sigma_n \beta_n$ where σ_n is a random scalar representing scale, and β_n is a random vector representing preference intensities. Under this specification, σ_n and β_n cannot be separately identified as variation in σ_n is clearly the same as perfectly correlated variation in β_n. For this reason, it is necessary to normalise either σ_n or β_n with the most common normalisation being to fix σ_n to one.

In the current paper, given the focus on scale, we make use of a model known as the scaled multinomial logit model (SMNL). In the SMNL model specification, the parameters representing preference intensities are treated as non random, whilst σ_n is assumed to be randomly distributed. Under a set of assumptions, the observed component of utility may be further expressed as

$$U_{nsj} = \sigma_n \bar{\beta} x_{nsj} + \varepsilon_{nsj}. \quad (3)$$

To estimate the model, the SMNL model assumes that σ_n is log-normally distributed with the further assumption that the $E\left[\sigma_n\right] = 1$ over the sampled population. The assumption that σ_n follows a lognormal distribution requires the estimation of parameters for the both the mean, μ, and variance, τ, population moments. The lognormal distribution, is expressed as follows.

$$\sigma_n = \exp\left(\mu + \frac{\tau^2}{2}\right). \quad (4)$$

In order to ensure $E\left[\sigma_n\right] = 1$, it is necessary to set $\mu = -\tau^2/2$ whilst the variance of the distribution is allowed to vary across the sampled population by taking draws from a standard normal distribution, z^d, which are then multiplied by the estimated parameter τ, such that

$$\sigma_n = \exp\left(-\frac{\tau^2}{2} + \tau z^d\right). \tag{5}$$

The model is flexible in that the variance of σ_n can be allowed to vary across different segments of the population via the introduction of additional terms in Equation (5) such that θ_q represents parameters associated with covariates w_q which can be used to decompose the scale parameter:

$$\sigma_n = \exp\left(-\frac{\tau^2}{2} + \theta_q \varpi_q + \tau z^d\right). \tag{6}$$

In the current paper, we interpret the model as if σ_n represents scale heterogeneity within the sampled population. As per our previous discussion however, we note an alternative interpretation to the modelled heterogeneity is possible given that σ_n may be perfectly correlated with the estimated preference intensities. Given that we have fixed the parameters associated with the preference intensities, it is therefore possible for any preference heterogeneity to now be captured, in part, or in total, by σ_n.

3. Empirical data

The data for the current study was collected in Australia in 2009 as part of a larger project designed to assess changes in vehicle purchasing behaviour in response to a vehicle emissions charging scheme, specifically the elasticity of demand for low emitting vehicles with respect to a CO_2 emission charge per kilometre and/or per annum per vehicle. A labelled choice experiment was most appropriate for this research given the interest in estimating alternative-specific effects for each of the fuel types used in the experiment. Nine attributes were included in the experiment, which were identified via a review of the available literature on vehicle purchasing, as well as through preliminary analysis of secondary data sources. Table 1 displays the levels that have been selected for each attribute. Note that the purchase price for the hybrid alternative is $3,000 more at each level in order to recognise that hybrid technology is currently more expensive than conventional fuel engines, and that the hybrid alternative is defined as a fuel source that is cleaner with respect to emission levels, rather than a specific type of fuel.

In establishing the choice profiles shown to respondents, a D-efficient design was used (Rose and Bliemer 2008). A reference alternative is included in the experimental design to add to the relevance and comprehension of the attribute levels being assessed by the individual respondents (Rose et al. 2008), and can be used to reduce hypothetical bias in stated preference surveys (Hensher 2010). An efficient experimental design requires optimisation over the values in the reference alternative. However, given that the exact specification of the vehicle each respondent recently purchased is not known *a priori*, it is not possible to present each respondent with a fully optimised design. However, an approximate method was used whereby all recent purchases were defined as being one of six different body sizes (small, small luxury, medium, medium luxury, large, large luxury) and one of two fuel types (petrol or diesel).

Table 1: Attribute levels for stated choice experiment

	Levels	1	2	3	4	5
Purchase Price	*Small*	$15,000	$18,750	$22,500	$26,250	$30,000
	Small Luxury	$30,000	$33,750	$37,500	$41,250	$45,000
	Medium	$30,000	$35,000	$40,000	$45,000	$50,000
	Medium Luxury	$70,000	$77,500	$85,000	$92,500	$100,000
	Large	$40,000	$47,500	$55,000	$62,500	$70,000
	Large Luxury	$90,000	$100,000	$110,000	$120,000	$130,000
Fuel Price	*Pivot*	-25%	-10%	0%	10%	25%
Registration	*Pivot*	-25%	-10%	0%	10%	25%
Annual Emissions Charge	Pivot off fuel efficiency of alternative. Each fuel efficiency had five possible values, with the average of the range increasing as fuel efficiency decreased					
Variable Emissions Charge	Pivot off fuel efficiency of alternative. Each fuel efficiency had five possible values, with the average of the range increasing as fuel efficiency decreased					
Fuel Efficiency (L / 100km)	*Small*	6	7	8	9	10
	Medium	7	9	11	13	15
	Large	7	9	11	13	15
Engine Size (cyl)	*Small*	4	6			
	Medium	4	6			
	Large	6	8			
Seating Capacity	*Small*	2	4			
	Medium	4	5			
	Large	5	6			
Country of Manufacture	*Random Allocation*	Japan	Europe	South Korea	Australia	USA

Consequently, each respondent received choice tasks from one of twelve possible designs, depending on what category their most recent purchase could be assigned to. Table 2 shows the "average vehicle" that was used for each category in generating each experimental design, and the d-error associated with each design. In calculating each design, an analytical approach was used whereby the asymptotic variance-covariance matrix was derived via the second derivatives of the log-likelihood function of the model to be estimated. To optimise this design, different combinations of attributes are trialled, and the design with the minimised d-error after repeated iterations is used. The iterations were allowed to run uninterrupted for several days.

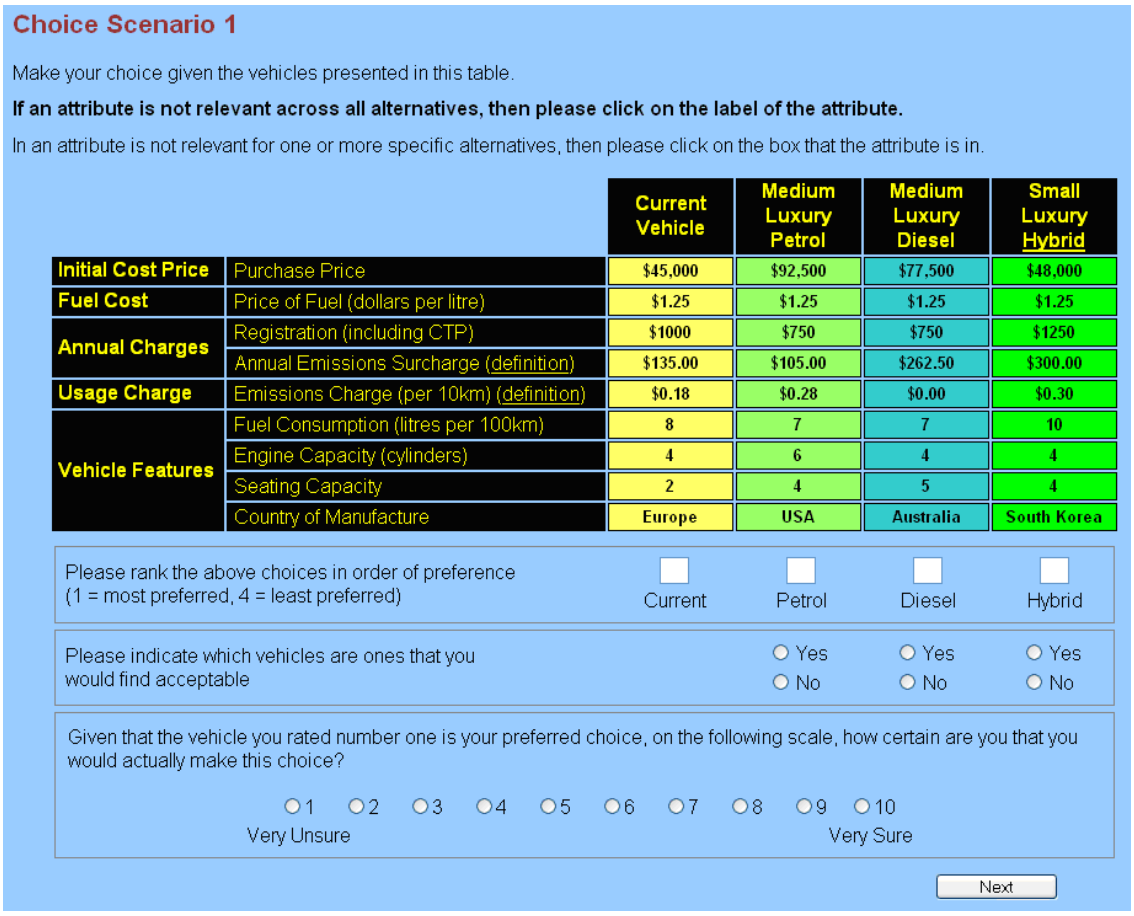
To ensure respondents were presented with realistic and sensible choice scenarios, a number of caveats were placed on the design. First, the annual and variable surcharge that is applied to an alternative is conditional on the type of fuel used and the fuel efficiency of the vehicle in question. Second, if the reference alternative is petrol (diesel), the petrol (diesel) fuelled alternative must have the same fuel price as the reference alternative. Third, the annual and variable surcharge for the hybrid alternative cannot be higher than that of another vehicle when the alternative vehicle has the same fuel efficiency rating or is more inefficient than the hybrid. Finally, to ensure that respondents faced a realistic choice task, given the size of the reference alternative, one of the remaining alternatives was randomly selected and restricted to be the same size as the reference, another was allowed to vary plus/minus one body size, and the third was allowed to vary freely.

Table 2: Average vehicle used for design optimisation

	Small		Medium		Large	
	Petrol	**Diesel**	**Petrol**	**Diesel**	**Petrol**	**Diesel**
Purchase Price	$25,000	$28,000	$33,000	$36,000	$40,000	$43,000
Fuel Price	$1.50	$1.65	$1.50	$1.65	$1.50	$1.65
Registration (incl. CTP)	$600	$600	$600	$600	$600	$600
Annual Emissions Charge*	--	--	--	--	--	--
Variable Emissions Charge*	--	--	--	--	--	--
Fuel Efficiency	8	8	10	8	12	10
Engine Capacity	4	4	4	4	6	6
Seating Capacity	4	4	5	5	5	5
Country of Manufacture	Japan	Europe	Japan	Europe	Australia	Europe
D-error	***0.012484***	***0.012343***	***0.012837***	***0.013201***	***0.014396***	***0.013616***
	Small Luxury		**Medium Luxury**		**Large Luxury**	
	Petrol	**Diesel**	**Petrol**	**Diesel**	**Petrol**	**Diesel**
Purchase Price	$31,000	$33,000	$45,000	$47,000	$75,000	$78,000
Fuel Price	$1.50	$1.65	$1.50	$1.65	$1.50	$1.65
Registration (incl. CTP)	$600	$600	$600	$600	$600	$600
Annual Emissions Charge*	--	--	--	--	--	--
Variable Emissions Charge*	--	--	--	--	--	--
Fuel Efficiency	8	8	10	8	12	10
Engine Capacity	4	4	4	4	6	6
Seating Capacity	4	4	5	5	5	5
Country of Manufacture	Japan	Europe	Japan	Europe	Australia	Europe
D-error	***0.013345***	***0.012756***	***0.013386***	***0.012485***	***0.016423***	***0.014807***

* Note that no values for the annual or variable charges were provided as inputs into the design, rather given the five levels linked to the fuel efficiency specified for the average vehicle outlined in Table Two, the allocation of these charges over the design was random, such that the D-error was minimised.

Respondents were required to complete a series of choice tasks, with each choice task containing three alternatives described by all of the attributes listed in Table 1, and were asked to rank their selections from most preferred to least preferred. As part of the choice task, respondents were able to indicate which alternatives within each task they found unacceptable. Such a question allows for models to be estimated where alternatives over which no trading behaviour occurred can be removed. An example of the choice screen is shown in Figure 1.



Choice Scenario 1

Make your choice given the vehicles presented in this table.

If an attribute is not relevant across all alternatives, then please click on the label of the attribute.

In an attribute is not relevant for one or more specific alternatives, then please click on the box that the attribute is in.

		Current Vehicle	Medium Luxury Petrol	Medium Luxury Diesel	Small Luxury Hybrid
Initial Cost Price	Purchase Price	$45,000	$92,500	$77,500	$48,000
Fuel Cost	Price of Fuel (dollars per litre)	$1.25	$1.25	$1.25	$1.25
Annual Charges	Registration (including CTP)	$1000	$750	$750	$1250
	Annual Emissions Surcharge (definition)	$135.00	$105.00	$262.50	$300.00
Usage Charge	Emissions Charge (per 10km) (definition)	$0.18	$0.28	$0.00	$0.30
Vehicle Features	Fuel Consumption (litres per 100km)	8	7	7	10
	Engine Capacity (cylinders)	4	6	4	4
	Seating Capacity	2	4	5	4
	Country of Manufacture	Europe	USA	Australia	South Korea

Please rank the above choices in order of preference (1 = most preferred, 4 = least preferred) — Current, Petrol, Diesel, Hybrid

Please indicate which vehicles are ones that you would find acceptable — Yes / No, Yes / No, Yes / No

Given that the vehicle you rated number one is your preferred choice, on the following scale, how certain are you that you would actually make this choice?

1 2 3 4 5 6 7 8 9 10
Very Unsure — Very Sure

Next

Figure 1: Stated preference task

4. Results

A total of 1,136 observations were collected for 142 respondents completing eight choice tasks each. It was necessary to remove seven choice tasks from the collected data due to data collection errors, leaving a total of 1108 usable observations. In terms of alternative acceptability, in 14 percent of choice tasks all alternatives were acceptable, in 46 percent one alternative was unacceptable, in 29 percent two alternatives were unacceptable and in eleven percent of choice tasks all three alternatives were unacceptable to respondents. The petrol alternative was unacceptable in 42 percent of choice tasks, the diesel alternative in 51 percent and the hybrid in 44 percent.

4.1 Analysis of certainty

Given that certainty ranged from *Very Unsure* (1) to *Very Sure* (10), respondents were reasonably certain about the choices they made, with an average of 7.20 and a standard deviation of 2.22. Figure 2 displays the distribution of certainty scores for the data set. The bounded nature of the certainty scale meant that an ordered logit model was most appropriate when exploring possible socio-demographic and attitudinal drivers of certainty. A recent study suggests there is no evidence that responses to the certainty index are random or systematically influenced by unobserved individual specific effects (Swardh, 2010) and similarly, we find that certainty scores do not appear to be random. Rather a number of individual characteristics prove to be significant in influencing the level of certainty respondents have about the choices that they make within the experiment. The results of the ordered logit are summarised in Table 3.

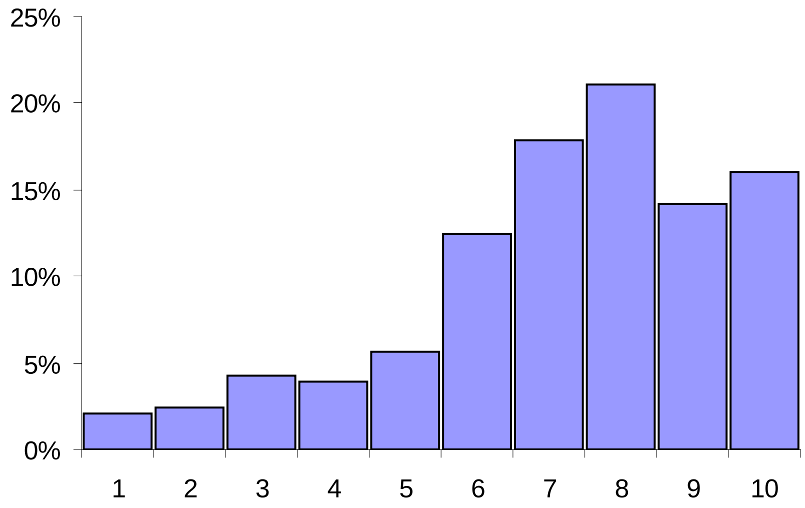


Figure 2: Certainty distribution

Table 3: Ordered logit – Drivers of certainty

Parameter Estimates (*t*-ratio)		
Part-time employed	-0.2399	(-2.196)
Not worked in past 6mths	1.1352	(7.298)
Age	0.0285	(4.098)
Hours worked per week	0.0147	(5.383)
Personal income	-0.0005	(-1.975)
Gender	0.2459	(3.431)
Household income	0.0003	(2.607)
Vehicles are a main cause of climate change	0.0969	(3.498)
People should be encouraged to use environmentally friendly transport	0.114	(3.626)
Government should implement carbon reduction policies	-0.0992	(-3.183)
Vehicle emissions charge is fair to all road users	0.0423	(2.188)
Model Fit Statistics		
LL(0)	-2341.103	
LL(β)	-2301.717	
Number of Respondents	142	
Number of Observations	1108	

Compared to fulltime workers, those who are part-time employed report lower certainty in their choices, whereas those who have not worked in the past six months are more certain about their responses than full time workers. Possible explanation for this result could be that part-time workers are in employment conditions that are more uncertain, thus their income is more uncertain. A car represents a sizeable cost to the purchaser with a long payment horizon, thus if you are not confident in how much money you have available to fund such a purchase either now or particularly in the future, it is understandable that you would be less confident in the choices that you make. On the other hand, those who have not worked in six months may be more assured of the choices they make given a more consistent financial situation or alternatively, they are an at home partner of a fulltime worker and is perhaps seeking to purchase a vehicle for a specific reason thus having a clearer view of the choices they wish to make.

Higher income earners are also more uncertain in the choices they make, and this could be a result of the fact that higher income means a lower budgetary constraint and thus a much wider range of possible options. Interestingly though, household income has an opposite impact where certainty increases as household income increases. A possible explanation is that high income households are more likely to have a range of different vehicles used for a specific purpose, or be able to purchase a vehicle specific to an individual user, thus making their choices more concrete. Males also report a greater level of certainty. Whilst a stereotype, it may be that males are more familiar with and engaged in the automobile market which allows them to make more confident choices.

With respect to attitudinal influences, environmental opinions were found to be significant in determining certainty. Respondents who agree with the statements that; vehicles are the main cause of climate change; people should be encouraged to use environmentally friendly transport; and a vehicle emissions charge is fair to all road users, report higher levels of certainty in their vehicle choices. This is likely a function of the fact that those who are more environmentally concerned with the role that the motor vehicle plays in climate change, are likely to have a very specific focus when selecting a vehicle (such as cars with better fuel efficiency or a cleaner and/or more efficient fuel source and so on) allowing them to respond with greater surety. Interestingly people who agree that the government should implement carbon reduction policies report lower levels of certainty in their vehicle choices. A potential explanation is that while a person may agree that a carbon reduction policy is needed, thus theoretically making them more environmentally conscious than others and hence one would expect a similar response as discussed previously, the nature of the carbon policy in many countries is unclear. Consequently, this uncertainty into exactly what policy may prevail may translate to uncertainty across choices because there is no clear criteria for which to evaluate vehicles.

4.2 Analysis of scale and certainty

To concentrate on the effect of scale heterogeneity, the SMNL has been employed. in the analysis of the vehicle choice data. Certainty enters Equation (6) as the covariate (w_q) used to decompose scale. Models with differing combinations of alternative specific and generic parameters where estimated in the process of identifying the best fitting models and 1,000 Halton draws were used in estimation. The results are presented in Table 4, where it can be seen that all parameters are of the expected sign. Less expensive vehicles are more attractive as is lower vehicle registration, and cars with a larger seating capacity are relatively more attractive, even more so for diesel automobiles. Sensitivity to the annual emissions surcharge is more pronounced in the hybrid alternative compared to petrol and diesel; the same is true for fuel efficiency. The positive constant for the hybrid alternative shows a positive disposition with respect to this type of vehicle compared to petrol, whereas for diesel the opposite is true.

Table 4: Model comparison – All alternatives

	Scale Only		*Scale as Function of Certainty*	
Parameter Estimates (*t*-ratio)				
No Choice Constant	-5.015	(-6.220)	-7.325	(-5.490)
Diesel Constant	-1.410	(-3.230)	-1.903	(-3.550)
Hybrid Constant	0.920	(2.200)	1.104	(2.170)
Vehicle Price ($'000)	-0.053	(-6.440)	-0.063	(-5.840)
Vehicle Registration	-0.0007	(-2.790)	-0.0008	(-2.540)
European Made Diesel	0.873	(3.510)	0.918	(3.110)
Annual Emissions Surcharge				
Petrol and Diesel	-0.0013	(-3.500)	-0.0017	(-3.350)
Hybrid	-0.0021	(-3.330)	-0.0030	(-3.620)
Fuel Efficiency				
Petrol and Diesel	-0.094	(-3.280)	-0.106	(-3.070)
Hybrid	-0.153	(-3.570)	-0.177	(-3.350)
Seating Capacity				
Petrol and Hybrid	0.322	(4.190)	0.309	(3.540)
Diesel	0.503	(4.430)	0.583	(4.200)
Scale Estimates				
Variance Parameter (τ)	1.274	(-8.010)	1.006	(7.080)
Scale Decomposition / Scale Decomposition (Certainty $\leq$ 5)	---	---	-1.701	(-5.100)
Sigma				
Sample Mean	0.944		0.802	
Sample Standard Deviation	0.998		0.970	
Model Fit Statistics				
Log-likelihood Restricted	-1391.708		-1371.821	
Log-likelihood Model	-1230.497		-1206.972	
McFadden ρ^2	0.115		0.120	
Info. Criterion: AIC	2.245		2.204	
Sample Size	1108		1108	

In the *Scale Only* model, it can be seen that scale is a significant factor in the choice of automobiles. To further understand potential systematic sources of scale, certainty was used to decompose this variable in a range of formats. Initially as a linear function of the original measurement scale, certainty proved to be significant, and substantially improved model fit. This result indicated that as levels of certainty decreased, the amount of scale heterogeneity across the choice tasks increased. However, alternative treatments of the certainty scale were trialled, such as dummy variables for different groupings and different threshold levels of certainty. The best result, as presented in Table 4, occurred when the certainty score was separated into a threshold level of scores of five or less versus six and above.

4.3 An analysis of scale, certainty and acceptable alternatives

An additional feature of the stated preference experiment was the ability for respondents to indicate which alternatives are unacceptable to them. An *a priori* expectation would be that in choice tasks where respondents are able to further narrow down the consideration set to a reduced number of alternatives, the amount of individual specific error exhibited by respondents should decrease. Similar to the modelling process for all alternatives, differing combinations of alternative specific and generic parameters were estimated in the process of identifying the best fitting models, which are presented in Table 5.

Table 5: Model comparison – Acceptable alternatives only

Scale Only

Parameter Estimates (*t*-ratio)		
No Choice Constant	-5.993	(-5.280)
Diesel Constant	-2.520	(-4.150)
Vehicle Price ($'000)	-0.042	(-5.260)
European Made Diesel	0.849	(2.880)
Annual Emissions Surcharge		
Petrol and Hybrid	-0.0012	(-2.500)
Fuel Efficiency		
Petrol and Hybrid	-0.124	(-3.360)
Seating Capacity		
Petrol	0.242	(3.300)
Diesel	0.384	(3.470)
Hybrid	0.309	(3.610)

Scale Estimates		
Variance Parameter (τ)	0.983	(6.340)
Scale Decomposition	---	---
Sigma		
Sample Mean	0.973	
Sample Standard Deviation	1.131	

Model Fit Statistics	
Log-likelihood Restricted	-826.482
Log-likelihood Model	-770.284
McFadden ρ^2	0.068
Info. Criterion: AIC	1.408
Sample Size	1108

Scale as Function of Certainty

Parameter Estimates (*t*-ratio)		
No Choice Constant	-11.677	(-9.110)
Diesel Constant	-3.420	(-4.070)
Vehicle Price ($'000)	-0.059	(-5.590)
European Made Diesel	1.105	(3.010)
Annual Emissions Surcharge		
Petrol and Hybrid	-0.0017	(-2.470)
Fuel Efficiency		
Petrol and Hybrid	-0.181	(-3.720)
Seating Capacity		
Petrol	0.324	(3.460)
Diesel	0.493	(3.100)
Hybrid	0.404	(4.090)

Scale Estimates		
Variance Parameter (τ)	1.165	(20.600)
Scale Decomposition (Certainty ≤ 5)	-2.128	(-7.140)
Sigma		
Sample Mean	0.807	
Sample Standard Deviation	1.324	

Model Fit Statistics	
Log-likelihood Restricted	-861.692
Log-likelihood Model	-738.624
McFadden ρ^2	0.143
Info. Criterion: AIC	1.353
Sample Size	1108

Whilst the parameters are again of the expected sign, what is immediately apparent is the reduced number of attributes that are significant when only the acceptable alternatives are used. This suggests that respondents, in eliminating alternatives, are focusing on a few key attributes they deem to be important, and alternatives which fail to reach some threshold level on these attributes are being designated as unacceptable. Focusing on the role of scale, the scale parameter is observed to be highly significant in the *Scale Only* model, indicating that respondent-specific error is not reduced even when looking at a reduced consideration set. Moreover, certainty (or lack thereof) has a bigger role in the model using only acceptable alternatives than the full alternative model. Similar to the *All Alternatives* model, certainty is found to be most significant at a threshold level of five or less. Thus, when people are uncertain about the choices they make, even after ruling out what they would never choose, the level of inconsistency observed in their responses is even greater. Intuitively, this result is behaviourally consistent; if you can eliminate alternatives but remain *unsure* about the choice you are making among those that remain, then these alternatives are likely to offer very similar levels of utility, essentially making the choice a “coin flip”.

Overall, reductions in the scale parameter (σ) mean that the utility function approaches zero ($V = \sigma\beta$), which in turn means that choices become more stochastic in nature. Conversely, as scale increases, choices are more attributable to changes in preferences (β) and thus are more deterministic. In both the *All Alternative* and *Acceptable Alternative Only* models, the negative parameter for the certainty index within the *Scale as a Function of Certainty* model indicates that when respondents report a certainty level of five or less (out of ten) in the choices they have made, the scale parameter is significantly smaller than for those choices made with greater certainty. That is to say, the choices made when certainty is lower are more stochastic in nature, which aligns with the *a priori* expectation.

4.4 Alternative approaches to handling certainty calibration

As discussed, a methodology commonly employed to reduce hypothetical bias in experiments is to calibrate models dependent on the level of certainty indicated by respondents about the choices they have made. In the previous analysis, behavioural consistency was found to be significantly less when certainty scores of five or less were reported. Given this finding, Table 6 presents the results for a choice model calibrated only on choice tasks where the level of certainty is above this threshold. Consistent with both models incorporating scale, when only acceptable alternatives are used in the choice task, the number of significant parameters is reduced along with the sensitivity of respondents to those parameters. However, it is also noticeable that the parameters which are significant in the calibrated model are different to those in the scale models.

Table 6: Model comparison – Certainty calibration approach

All Alternatives

Parameter Estimates (*t*-ratio)		
No Choice Constant	-3.171	(-10.720)
Hybrid Constant	2.227	(5.250)
Vehicle Price ($'000)	-0.033	(-12.180)
European Made Diesel	0.520	(2.500)
Diesel Engine Capacity	-0.202	(-2.960)
Fuel Price ($/litre)		
Diesel and Hybrid	-0.803	(-3.650)
Annual Emissions Surcharge		
Petrol and Diesel	-0.0011	(-3.650)
Hybrid	-0.0025	(-4.230)
Fuel Efficiency		
Petrol	-0.072	(-2.810)
Diesel	-0.177	(-5.370)
Seating Capacity		
Petrol and Hybrid	0.221	(4.230)
Diesel	0.454	(5.650)

Model Fit Statistics	
Log-likelihood Restricted	-1138.556
Log-likelihood Model	-969.714
McFadden ρ^2	0.148
Info. Criterion: AIC	2.177
Sample Size	903

Acceptable Alternatives Only

Parameter Estimates (*t*-ratio)		
No Choice Constant	-3.572	(-14.430)
Hybrid Constant	1.366	(3.520)
Vehicle Price ($'000)	-0.023	(-7.240)
European Made Diesel	0.730	(2.730)
Diesel Fuel Price ($/litre)	-1.702	(-5.820)
Diesel Seating Capacity	0.368	(4.660)
Hybrid Fuel Efficiency	-0.118	(-3.030)
Annual Emissions Surcharge		
Petrol and Diesel	-0.0014	(-3.560)
Hybrid	-0.0025	(-3.530)

Model Fit Statistics	
Log-likelihood Restricted	-658.850
Log-likelihood Model	-596.292
McFadden ρ^2	0.095
Info. Criterion: AIC	1.341
Sample Size	903

Another approach via which respondent certainty can be used to calibrate model results is to probability weight the choice tasks as a function of the certainty of choice made in each specific task. Under this approach, choice tasks with a greater level of certainty are assigned a greater weight and those with lesser respondent certainty are given less weight. The results of these models are presented in Table 7 and again, what is immediately obvious is that the number and combination of significant parameters in both the *All Alternatives* and *Acceptable Alternatives Only* models are starkly different to those in both scale models and the certainty calibration results.

Table 7: Model comparison – Certainty probability weight

All Alternatives

Parameter Estimates (*t*-ratio)		
No Choice Constant	-3.260	(-21.690)
Diesel Constant	-0.921	(-3.690)
Hybrid Constant	1.565	(7.450)
Vehicle Price ($'000)	-0.032	(-35.270)
Fuel Price		
Diesel	-0.367	(-2.780)
Hybrid	-0.527	(-4.410)
Registration		
Petrol	-0.0004	(-5.320)
Diesel	-0.0005	(-6.410)
Hybrid	-0.0002	(-2.660)
Annual Emissions Surcharge		
Petrol and Diesel	-0.0010	(-9.690)
Hybrid	-0.0023	(-11.380)
Variable Emissions Surcharge		
Diesel	-1.409	(-5.410)
Hybrid	-0.704	(-2.830)
Engine Capacity		
Petrol	0.058	(2.670)
Diesel and Hybrid	-0.090	(-5.580)
Fuel Efficiency		
Petrol and Hybrid	-0.1204	(-15.290)
Diesel	-0.0274	(-2.150)
Seating Capacity		
Petrol and Hybrid	0.218	(11.890)
Diesel	0.485	(17.240)
Petrol Australian Made	-0.260	(-3.830)
Japanese Made		
Petrol	0.245	(3.630)
Diesel	-0.394	(-4.810)
European Made		
Petrol and Hybrid	0.253	(5.440)
Diesel	0.535	(7.330)

Acceptable Alternatives Only

Parameter Estimates (*t*-ratio)		
No Choice Constant	-2.654	(-13.100)
Hybrid Constant	2.118	(9.290)
Vehicle Price ($'000)	-0.024	(-21.060)
Annual Emission Surcharge	-0.0013	(-10.950)
Diesel Variable Emissions Surcharge	-0.994	(-3.190)
Fuel Price		
Petrol	0.440	(3.260)
Diesel	-0.741	(-5.300)
Registration		
Petrol and Hybrid	-0.0002	(-3.530)
Diesel	-0.0004	(-4.930)
Fuel Efficiency		
Petrol	-0.074	(-5.870)
Hybrid	-0.142	(-9.910)
Engine Capacity		
Petrol	0.080	(2.720)
Diesel and Hybrid	-0.111	(-5.480)
Seating Capacity		
Petrol	0.114	(3.350)
Diesel	0.505	(15.130)
Hybrid	0.237	(8.090)
Japanese Made Petrol	0.406	(4.740)
European Made		
Petrol	0.384	(4.460)
Diesel	0.831	(8.790)
South Korean Made		
Diesel	0.328	(3.350)
Hybrid	-0.432	(-5.200)

Table 7: Model comparison – Certainty probability weight (cont.)

All Alternatives

Model Fit Statistics	
Log-likelihood Restricted	-10293.024
Log-likelihood Model	-8775.926
McFadden ρ^2	0.147
Info. Criterion: AIC	15.875
Sample Size	1108

Acceptable Alternatives Only

Model Fit Statistics	
Log-likelihood Restricted	-5985.060
Log-likelihood Model	-5371.782
McFadden ρ^2	0.102
Info. Criterion: AIC	9.734
Sample Size	1108

To examine if the differences in the parameter estimates are the result of a scale factor, the ratio of directly comparable parameter estimates have been obtained, where the results from the models accounting for scale are contrasted with their respective models where certainty calibration was used, and where probability weighting was employed. These results are present in Figure 3.

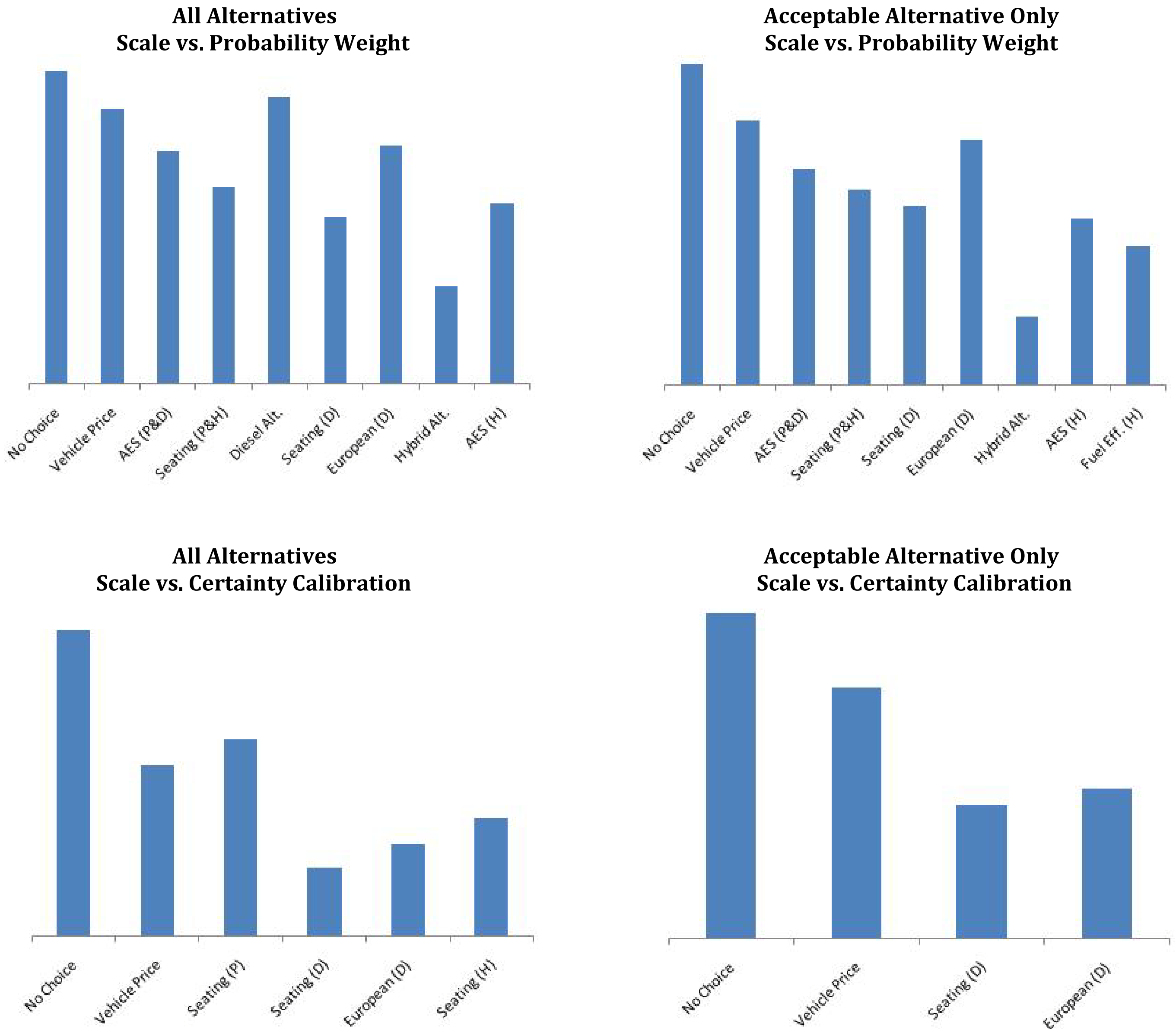


Figure 3: Ratio of comparable model parameters

If the difference in the observed parameters was a function of a constant scale factor, then one would expect the ratio of parameters to be more or less the same across all the paired combinations. What is observed in Figure 3, however, are a series of ratios that differ quite dramatically when comparisons are made between models where scale as been accounted for and where it has not. These results indicate that, without a constant scale factor applied to the parameters, the ratio of any two parameters within one modelling approach will be different to the same ratio if a different approach is used. That is to say, the willingness to pay statistics will differ from model to model, depending on what methodology is employed by the researcher.

Discussion and conclusion

This paper shows respondent certainty to be a complex variable that is a function of many of the characteristics and attitudes of the respondent themselves. Consequently, using certainty in trying to understand the origin of any scale heterogeneity that may exist within the choices of respondents, provides a unique opportunity given the amount of information that can be captured through the parsimonious use of this construct. It should be noted that certainty is a different concept to familiarity with the choice task however, respondents may be more or less familiar with the task itself, but at the same time be more (or less) certain as to which alternative they would be most likely to choose if confronted with a similar choice situation in real life.

In attempting to understand what might influence the amount of idiosyncratic error that exists across choice tasks, the specification of the certainty index that resulted in the best fit was a dummy variable separating choice tasks where scores of five or less were reported versus scores of six and above. This result suggests that rather than decreases in certainty linearly decreasing the amount of scale observed, there is a threshold level of certainty below which the choices made by respondents become significantly less consistent. Certainty in choices being subject to some threshold level is a phenomenon that is found in other research. For example, Champ et al. (1997) and Blumenschein et al. (2001) found that including only those who responded with a ten produced a mean willingness to pay that was equivalent to actual willingness to pay. On the other hand Champ and Bishop (2001) and Norwood (2005) found that eight was an appropriate threshold, whereas Ethier et al. (2000) and Poe et al. (2002) found that a threshold of seven was a sufficient condition. Whilst these studies also employing a ten point rating scales have shown the existence of an appropriate certainty threshold, the combined research suggests that the threshold point differs and as a consequence the selection of the threshold itself remains somewhat arbitrary (Morrison and Brown 2009).

In this paper we have examined three different approaches to the treatment of response certainty; decomposing scale by certainty; calibrating the model based on responses that obtained a threshold level of certainty; and weighting responses based on the certainty score assigned to those responses. However this paper only utilises one treatment of the certainty index itself, though several variations of measuring respondent certainty exist. For example, Li and Mattsson (1995) used a scale from 0-100 percent where the certainty level increases in increments of five percent. Blumenschein et al. (1998) used a two-category qualitative scale that allowed respondents to indicate whether they were “probably sure” or “definitely sure” about their prior response and Johannesson et al. (1998) used the categories “fairly sure” and “absolutely sure”.

Originating from the contingent valuation framework, the use of the certainty index as a method of reducing hypothetical bias in choice experiments is becoming increasingly more prevalent, particularly in the environmental literature. However, what is lacking in the stated preference framework is a coherent theoretical argument as to how the certainty index should be employed. This paper has shown that in using only one method of measuring certainty, the index itself can be employed in several different ways, with each modelling approach resulting in substantially different parameter estimates. Additionally, it is equally possible that the different ways in which certainty can be measured will also result in the diverse outcomes observed in this paper when each index is employed using a different modelling approach; moreover differences may also be observed as a result of using the different measurement scales themselves within the same modelling process. Thus, until such questions are answered and an appropriate framework is developed, the value of a certainty index remains unclear. It should also be recognised that the subjective response on the certainty scale is itself subject to response error.

Further, in attempting to determine which model produces the "best" outcome, the researcher may be tempted to use the model fit statistics in order to arrive at a conclusion. For example, when comparing models with all alternatives to the acceptable alternatives only model, there is a consistent improvement in the model fit across the scale models, certainty calibration models and probability weighting models. Thus, the intuitive assumption is that the acceptable alternative only model is a better representation. However, in removing alternatives from the choice tasks the way in which the probabilities are being determined across the alternatives differs, which in turn means that the log-likelihood function that is being optimised in the acceptable alternatives only model is different to that in the all alternatives model. Likewise, the model fit statistics appear to be superior for the model where the choice tasks that failed to meet the threshold level of certainty are removed, leading one to conclude that this would be the best approach. However, removing choice tasks from the sample means that the summation of the log-likelihood function is now occurring over a reduced number of observations. Thus, what could be assumed to be improvements in model fit as a result of better behavioural representation may in fact be the results of econometric differences in the model.

Econometric issues aside, there are also behavioural considerations that need to be taken into account. A fundamental difference between stated preference and revealed preference behaviour is the way in which information is gathered and considered. In a revealed preference sense, respondents are free to gather information on all the alternatives they deem relevant and completely ignore, or chose not to collect, any information on an alternative deemed unacceptable. In a stated preference experiment, however, they are presented with the information and then use that information to determine if an alternative is acceptable or not, typically with analyst assuming that this information is not ignored in a stated preference experiment. Specifically, designating an alternative as unacceptable does not mean that it was not considered or evaluated when making a choice. Given that utilities are calculated relative to the alternatives and attribute levels within a choice task, removing data from a choice task may be questionable if a true representation of respondent behaviour is desired.

In examining scale, alternative acceptability and response certainty, this paper has highlighted not only a number of directions for future research, but also areas in which the analyst should use caution. In using a scaled multinomial logit to highlight the role that scale plays in the choice process, this paper has shown the intuitively appealing result that as respondent certainty about their choices decreases, the choices themselves become less deterministic. However, a potential limitation of this study is that in such methodology, the scale and preference estimates are confounded. Thus, it is possible that what is being observed as changes in scale may be changes in preference sensitivity, which are perfectly correlated with scale. Future research will incorporate more advanced modelling techniques that will seek to disentangle the two effects more fully.

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