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On the use of flexible mixing distributions in WTP space: an induced value choice experiment*

Claudia Bazzani, Marco A. Palma and Rodolfo M. Nayga Jr†

In this study, we use data from an induced value choice experiment to compare estimates from mixed logit models in willingness to pay (WTP) space using different parameter distributional assumptions. Specifically, we test differences in WTP estimates when using flexible parameter mixing distributions (i.e. Legendre polynomials, step functions and splines) and conventional parameter distributions (normal and lognormal). Similar WTP estimates are obtained. However, we observe that WTP estimates are statistically different from the induced value when conventional distributions are assumed, but they are not when more flexible distributions are assumed. This suggests that flexible distributions can provide more reliable WTP estimates.

Key words: flexible mixing distribution, induced value choice experiment, normal distribution, WTP space.

1. Introduction

Discrete choice experiments (DCEs) are a widely used stated preference method in marketing and applied economics. In DCEs, respondents are presented with several hypothetical purchasing scenarios representing product alternatives which differ in terms of attributes, attribute levels and price. In each choice scenario, individuals are generally asked to make trade-offs between the product alternatives and an opt-out option. Their popularity in assessing consumers' willingness to pay (WTP) is given by a number of reasons. First, DCEs allow researchers to simulate a decision mechanism which closely resembles how individuals usually make their choices in real purchasing situations and to simultaneously estimate consumer preferences for different product attributes (Gracia *et al.* 2011; Akaichi *et al.* 2013; Bazzani *et al.* 2017).

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†Claudia Bazzani (e-mail: claudia.bazzani@univr.it) is at Department of Business Administration, University of Verona, Via Cantarane, 24 - 37129, Verona, Italy. Marco A. Palma is at Department of Agricultural Economics, Texas, 2124 Texas A&M, College Station, TX, USA. Rodolfo M. Nayga is at Department of Agricultural Economics and Agribusiness, University of Arkansas, 217 Agriculture Building, Fayetteville, AR, USA.

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Second, DCEs are consistent with long-standing theories of consumer choice behaviour, which are the random utility theory and the Lancaster theory (Luce 1959; McFadden 1974; Louviere *et al.* 2010). Third, the experiments are flexible, and they can be presented in many different formats. Estimates from random utility-based discrete choice models can then be translated into marginal WTPs for the product attributes. The estimation of reliable WTP values is important since these can be used not only for product marketing and pricing decisions but also for welfare analysis and policymaking.

In order to obtain more reliable WTP estimates from DCEs, different methodological and estimation issues have been tested. Discrete choice models (DCMs) that account for random taste parameters, such as the mixed logit models, are now routinely used due to improvements in computing power and speed (Train 2003; Scarpa *et al.*, 2005). Mixed models can be estimated by specifying the utility parameters in preference space or in WTP space. In preference space, researchers can derive the WTPs for nonprice attributes by taking the negative of the ratios of the nonprice attributes coefficients and the price coefficient. In WTP space models, the utility is reparameterised so that the attribute coefficients can be directly interpreted as marginal WTPs (Cameron and James 1987; Train and Weeks 2005; Scarpa *et al.* 2008a; Scarpa and Willis 2010; Carson and Czajkowski 2013). In WTP space models, the price/scale coefficient can be treated as random in order to overcome the confounding distributional assumptions of price and scale parameters (standard deviation of the unobserved utility) that usually occur in preference space due to the specification of the price as a fixed parameter. Specifying the price as a fixed parameter implies that the standard deviation of the unobserved utility does not vary over observations. The variation in scale might be confounded with the variation in WTP, which would imply inaccurate interpretation of the WTP estimates (Train and Weeks 2005; Scarpa *et al.* 2008a). Past studies report that models estimated in WTP space provide more stable and reasonable WTP estimates than models in preference space (e.g. Train and Weeks 2005; Balcombe *et al.* 2009; Thiene and Scarpa 2009). Thus, researchers from several areas, such as food, environment, health and transport economics have been increasingly turning to the estimation of models in WTP space (Scarpa *et al.* 2008a; Daly *et al.* 2012; Hole and Kolstad 2012; de-Magistris *et al.* 2013; Bazzani *et al.* 2017; Caputo *et al.* 2017).

However, some studies show a decrease in model fit when models are estimated in WTP space instead of in preference space (Train and Weeks 2005; Sonnier *et al.* 2007). According to Train and Weeks (2005), this may be due to the utilisation of commonly used convenient distributions (i.e. normal and lognormal) of the attributes' parameters[1]. For this reason, there is

[1] Specifying nonprice attribute coefficients with normal distribution and the price coefficient with a log-normal distribution implies that WTP for the attribute is distributed as the ratio of a normal to a log-normal. If a researcher works directly in WTP, this represents an inconvenient WTP distribution (Train and Weeks 2005)

increasing attention being paid to the use of commonly used distributions of the parameter distribution in WTP space (Train and Weeks 2005; Train 2016). We focus on this important issue in this study by using data from a real nonhypothetical induced value choice experiment (IVCE) to estimate WTP space models with different forms of parameter distribution.

Findings from previous studies show that the use of flexible mixing parameter distributions affects model performance and WTP estimates (Fosgerau and Bierlaire 2007; Burda *et al.* 2008; Scarpa *et al.* 2008b; Train 2008, 2016; Fosgerau and Hess 2009; Bastin *et al.* 2010; Fox *et al.* 2011; Fosgerau and Mabit 2013; Fosgerau 2014). Bastin *et al.*, Fosgerau and Bierlaire (2007), Fosgerau and Hess (2009), Fosgerau and Mabit (2013) and Fosgerau (2014) tested that the specification of parameter distribution with Legendre polynomials significantly improved model fit in comparison with models where a normal distribution was specified. Scarpa *et al.* (2008b) observed that the use of polynomial distributions improved model performance and also captured significant interaction effects between the experimental attributes. This suggests that the implementation of flexible distributions impacted WTP estimates. Burda *et al.* (2008) obtained model flexibility by using a normal Kernel distribution with a skewing function and showed that the semiparametric model captured a richer preference structure. Finally, Bajari *et al.* (2007), Train (2008) and Fox *et al.* (2011) documented that the use of continuous nonparametric distributions had computational advantages in the estimation of discrete choice models.

While results from these studies are based on estimates from models in preference space, Train (2016), Bansal *et al.* (2016) and Franceschinis *et al.* (2017) implemented flexible distributions (i.e. Legendre polynomials, splines and step functions) to estimate models in WTP space. In these studies, the authors found variations in model performance and WTP estimates when flexible distributions were specified. However, these three studies tested the use of flexible distributions using estimates from 'home-grown value' experiments. In home-grown value experiments, the value of the good is known to the respondent, but not to the experimenter. Hence, the experimenter would not know whether the respondent is really providing truthful choices. On the other hand, in induced value experiments, the value of the good is known to the respondents and to the experimenter, and so the respondents should not have uncertainty in defining their value for the good in question (Smith 1976). Therefore, in contrast to previous studies, we use the induced value experiment approach to determine which assumption of the parameter distribution gives estimates equal or closer to the theoretical predictions. Theoretically, more reliable WTP estimates should then be equal or closer than less reliable ones to the induced value. Hence, we posit that in a context in which it is important to test whether WTP values are accurate, modelling flexible distributions of the utility parameters of the actual data will be critical.

In this study, we explore whether the use of WTP space models with richer flexible distributions of the random parameters would affect the reliability of

WTP estimates when the theoretical value of the parameters is known. We, then, test whether the use of flexible or conventional distributions provides WTP estimates equal or closer to the induced value in order to determine which kind of distributions provide more accurate WTP estimates in WTP space models. Specifically, we estimate the semiparametric logit-mixed logit model (LMLM) proposed by Train (2016), with specification of Legendre polynomials, splines and step functions to model the distributions of the random parameters. We then compare the WTP estimates from these models with the estimates from a second-degree polynomial, which essentially assumes normally and lognormally distributed coefficients. Results suggest that the use of flexible distributional assumptions of the WTP space parameters can provide more accurate and reliable WTP estimates. Although the magnitudes of the parameters using conventional distributions (i.e. normal and lognormal) are not very different from those using more flexible distributions, the WTP estimates from the models using conventional distributions would have been misleading and ultimately wrong.

2. Materials and methods

2.1 Experimental design

Data were collected from a laboratory experiment conducted at a major research university. Students were invited to participate in an economic experiment focused on the investigation of individuals' choice behaviour. They were informed that they would receive a compensation of $8 for their participation and that they would have the opportunity to increase their earnings based on their decisions during the experiment. Fifty-three students participated in our induced value choice experiment (IVCE).

Following Luchini and Watson (2014), fictitious goods, that is *tokens*, were used as the product in question. As reported in Table 1, the tokens differed in terms of *colour* (red/blue), *shape* (triangle/square) and *price* ($0.5, $1.5, $2.5, $3.5). The value of the colours and shapes were known to the respondents[2] .

Using a D-optimal design (Street and Burgess 2007), attributes and attribute levels were allocated in eight choice sets with a 96.6 per cent D-efficiency. Each choice set was characterised by two token alternatives and a 'none of these' options. For each choice set, participants were asked to make a trade-off between the two token alternatives and the 'none of these' alternatives. The value of each token alternative was given by the sum of the values of the attributes' levels minus the price of the token (Table 1). The final earning that participants could gain from the choice of one of the two token alternatives was equal to the sum of the value of the token relative to the initial $8. On the other hand, the value of the opt-out alternative was equal to the $8 participation fee. Students were given a copy of the

[2] See the experimental instructions available in the Appendix S1.

Table 1 Attributes and attribute levels of the IVCE

Attributes	Levels	Value of the attribute ($)
Price	$ 3.50	$ 3.50
	$ 2.50	$ 2.50
	$ 1.50	$ 1.50
	$ 0.50	$ 0.50
Colour	Red	$ 3.00
	Blue	$ 1.00
Shape	Triangle	$ 4.00
	Square	$ 2.00

experiment instructions which were also read aloud by the experimenter. The instructions explained how to calculate the value of the choice alternatives (two tokens and the opt-out alternative) (see Appendix S1). The objective of the participants was to gain the maximum possible earnings by choosing the alternative with the highest pay-off. The experiment was incentive compatible, and one of the choice sets was randomly selected as binding. At the end of the experiment, a participant picked a card from a randomly arranged deck of eight cards, which represented the eight choice sets. The randomly picked card represented the binding choice set and each respondent gained the amount of money equal to the value of the alternative he/she chose in the binding choice set.

The instructions were followed by a practical example and a quiz to test respondents' understanding of the mechanism. After the quiz, the answers to each question were reviewed. In addition, following Collins and Vossler (2009), subjects were incentivised to carefully read the instructions and answer the quiz questions. A bonus of $2 was offered to participants if they answered all the quiz questions correctly.

2.2 A semiparametric logit-mixed logit model in WTP Space

In random utility models, the utility for person n given by the choice of alternative j at choice situation t can be specified as follows:

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt} \tag{1}$$

where x_{njt} is a vector of observed attributes, β_n' is the vector of structural taste parameters which vary over all observations and ε_{njt} is a random term that represents the unobservable portion of the utility.

The deterministic part of the utility function ($\beta_n' x_{njt}$) can be separated in price and nonprice attributes. In particular, in WTP space models, marginal WTP values enter in the utility function given that the utility coefficients vary over individuals. Following Train (2016), the utility that individual n derives in choosing alternative j at choice situation t can be expressed as follows:

$$U_{njt} = -\sigma_n(p_{njt} + wtp'_n x_{njt}) + \varepsilon_{njt} \tag{2}$$

where p_{njt} is price, wtp_n is a vector of WTP for each nonprice attribute, and σ_n is a random scalar. Note that $\sigma_n = \pi_n/k_n$, where π_n is the price coefficient in preference space and k_n is the scale parameter of individual n; $wtp_n = \gamma_n/\sigma_n$ and γ_n is the vector of nonprice coefficients in preference space; ε_{njt} is the random error that accounts for the unobserved portion of the utility. The probability that alternative i is chosen by the individual n among a sequence of choices from t = 1,...,T conditional on β_n is:

$$Q_{nit}\{\beta_n\} = \frac{e^{-\sigma_n(p_{nit}+wtp\prime_n x_{nit})}}{\sum_{j\in J} e^{-\sigma_n\left(p_{njt}+wtp\prime_n x_{njt}\right)}} \tag{3}$$

where β_n is the corresponding vector of utility coefficients and is defined as the vector of σ_n and wtp_n. The cumulative distribution function of utility parameter β_n and of distributional parameter α is $F(\beta|\alpha)$. F can be defined discrete with a finite support set S. Thus, for any $\beta_r \in S$, the probability mass function of F can be specified as follows:

$$W(\beta_r/\alpha) = \frac{e^{\alpha\prime z(\beta_r)}}{\sum_{s\in S} e^{\alpha\prime z(\beta_s)}} \tag{4}$$

where $z(\beta_\mathrm{r})$ is the vector capturing the distributional shape of the mass function mixing distributions which can be represented as a logit function of higher order Legendre polynomials, splines or step functions.

The associated log-likelihood function can then be defined as follows:

$$\mathrm{LL} = \sum_{n=1,\ldots N}^{N} \ln\left(\sum_{r\in S} L(\beta_r) W(\beta_r/\alpha)\right) \tag{5}$$

Given the large size of S, it is unfeasible to calculate the log-likelihood function. As such, the Log-likelihood function is simulated using random draws for each individual β_r. The procedure is implemented in MATLAB using the code in Train (2016) with 2000 random draws.

3. Results

With *Colour* and *Shape* being coded as dummy variables, we estimated the marginal WTPs for the *colour* and *shape* attributes, using the 'lower' value levels (blue and square) as baseline. Hence, the 'marginal' induced value that respondents should be willing to pay for an attribute of the token is equal to the difference between the value of the two levels of the attribute, that is \$2, both in the case of the *red* and *triangle* attributes (Collins and Vossler 2009). Given that the theoretical predictions of the marginal WTP (MWTP) estimates are equal to \$2 for the *red* colour and the *triangle* shape, our hypotheses are therefore the following:

$$H_{01}: \text{MWTP Red colour} = 2,$$

$$H_{02}: \text{MWTP Triangle Shape} = 2.$$

We posit that if H_{01} and H_{02} are not rejected, reliable WTP estimates are obtained since the MWTPs for red and triangle tokens are equal to the induced value theoretical predictions.

The MWTPs for *red* and *triangle* tokens were estimated using the semiparametric logit-mixed logit model (LMLM) (Train 2016). First, we estimated the model employing a normal distribution, that is second-degree polynomial (2poly-LMLM). Then, in order to provide more flexible distributions of the random parameters, we estimated models with the specification of higher order Legendre polynomials, splines and step functions. For each kind of z-function, we selected the form which provided a significant improvement in model fit on the basis of the log-likelihood ratio test. Specifically, we selected models with four-degree polynomial (4poly-LMLM), two knots splines (2splines-LMLM) and five levels step function distributions (5step-LMLM), respectively, since the log-likelihood ratio test showed that the addition of extra parameters did not significantly improve model performance.[3] In Table 2, we report information criteria across the four models.

Table 2 shows that when more flexible distributions are specified, an increase in the LL function is observed indicating an improvement in model fit. This result is consistent with the studies of Fosgerau and Hess (2009), Bajari *et al*. (2007) and Franceschinis *et al*. (2017) who showed that model performance improved with the specification of more flexible distributions. We observe that 4poly-LMLM and 2splines-LMLM outperform the 2poly-LMLM in terms of AIC statistics, while this is not happening in the case of the 5level-LMLM. In addition, model fit does not improve in terms of BIC statistics with the specification of more flexible distributions. This result is consistent with the study of Bansal *et al*. (2016) who observed a decrease in model performance in terms of BIC values when the number of extra parameters specified in the mixing distributions increased. Similarly, our results suggest that the increase in log-likelihood function due to the addition of extra parameters might not necessarily be enough to improve BIC values. This is actually not surprising given the fact that BIC measures aim at finding the true model among a set of candidates and therefore might not handle high dimensions or complex models well. It is also important to point out that BIC and AIC statistics are used in the estimation of structural parameters. In the

[3] Results are available upon request to the authors.

Table 2 Models

Distribution	No. of observations	No. Parameters	Log-likelihood	AIC	BIC
Normal					
Two-degree Polynomial	424	11	−117.382	256.764	301.311
Flexible					
Four-degree Polynomial	424	19	−106.798	251.596	328.540
Two-knots Splines	424	21	−102.958	247.916	332.960
Five-levels- Step Function	424	25	−104.158	258.316	359.559

case of nonparametric or semiparametric models, such as the semiparametric LMLM, nuisance parameters could also be counted as model parameters. Hence, the BIC and AIC statistics might be unsuitable to be part of model fit information criteria.

In regard to model estimates, Table 3 shows that mean coefficients of the red colour and triangle shape attributes are similar across the models.

In order to test whether the estimates are equal to 2, that is the induced value, we compare the means of red colour and triangle shape parameters to a value equal to 2 and apply a t-test to test whether the mean parameters are different from the induced value at the 10 per cent level of significance. For each model specification, we report *P*-values of the t-test between the mean values of red and triangle mean parameters and the induced value. A *P*-value equal or higher than 0.10 indicates that the hypothesis of equality between the mean coefficients and the induced value cannot be rejected. Results from Table 3 show that when flexible distributions are implemented, there is no evidence that the hypothesis of equality with the induced value fails, since the MWTPs for red and triangle attributes are not statistically different from 2. On the other hand, when a normal distribution is specified, the hypothesis of equality with the induced value is rejected. This suggests that, in some cases, small differences may be important for the hypothesis being tested. We then deduce that more reliable WTP estimates can be obtained when flexible distributions are specified.

It is also important to point out that the standard deviations of red colour and triangle shape attributes in the 4poly-LMLM and of the triangle shape attribute in the 5step-LMLM are respectively not statistically significant showing homogeneity of the attribute valuations around 2. In the case of the 2splines-LMLM, the standard deviation of the triangle shape attribute is not significant, but the parameter mean estimates suggest that the WTP distributions should be more centred around a slightly lower value than 2, that is, 1.8. This is also illustrated in Figures 1 and 2 which report the actual WTP distributions of the four model specifications.

Distributions of red colour and triangle shape MWTP from the 4-poly-LMLM and of the triangle shape in the 5step and 2splines LMLM have, indeed, a more homogeneous distribution. Specifically, distributions from 4poly-LMLM of both attributes MWTP and 5step-LMLM triangle shape

Table 3 Parameter estimates in WTP space of normal and flexible mixing distribution of the random parameters

	Normal (Two-degree Polynomial)	Hypothesis test of equality to 2 (*P*-value)	Flexible (Four-degree Polynomial)	Hypothesis test of equality to 2 (*P*-value)	Flexible (Splines, two knots)	Hypothesis test of equality to 2 (*P*-value)	Flexible (Step function, five levels)	Hypothesis test of equality to 2 (*P*-value)
Variable								
Means								
Red	2.724*** (0.244)	0.003	1.951*** (0.396)	0.902	1.772*** (0.318)	0.473	1.952*** (0.269)	0.749
Triangle	2.804*** (0.307)	0.008	2.036*** (0.367)	0.921	1.773*** (0.289)	0.432	2.086*** (0.242)	0.750
Price	1.553*** (0.130)		1.540*** (0.127)		1.603*** (0.143)		1.627*** (0.270)	
No Purchase	−2.293** (1.035)		−4.191*** (1.090)		−3.305*** (1.194)		−4.929** (1.340)	
Standard Deviations								
Red	0.198*** (0.073)		0.069 (0.045)		0.542*** (0.085)		0.394*** (0.118)	
Triangle	0.063 (0.110)		0.080 (0.095)		0.111 (0.146)		0.130 (0.170)	
Price	0.653*** (0.106)		0.663*** (0.132)		0.613*** (0.116)		0.522*** (0.119)	
No Purchase	1.536** (0.683)		1.234* (0.656)		0.299 (0.487)		1.699*** (0.455)	

Note ***, ** and * indicate that parameters are different from 0 at 1%, 5% and 10% of significance level, respectively

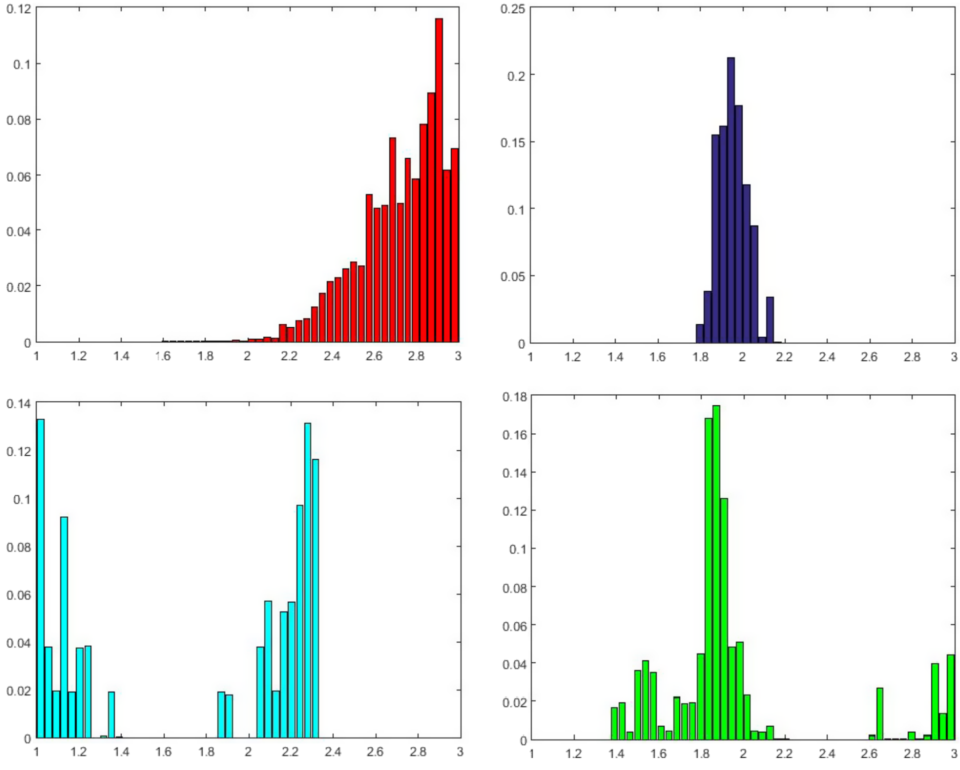

Figure 1 WTP distributions of the Color Coefficient for 2-degree polynomial (red), 4-degree polynomial (blue), 2-knots spline (cyan) and 5-step function (green).[Colour figure can be viewed at wileyonlinelibrary.com]

MWTP are more centred on 2 in comparison with the 2poly and 2splines LMLMs. As expected, WTP distributions from the 2poly-LMLM comprise values greater than 2. Moreover, the colour parameter distribution is particularly right skewed suggesting that the conventional normal distribution might not appropriately fit the true model distribution. This result corroborates the conjecture of past studies (Cherchi and Polak 2005; Train and Sonnier 2005; Balcombe *et al*. 2009) that the use of wrong distributions could lead to biased model estimates, since estimates from the 2poly-LMLM are statistically different from the induced value. However, from Figure 1, we can observe that when the 2-knots spline is assumed, the MWTP for the red colour attribute distribution appears bimodal instead of unimodal and centred on 2 as expected. If we turn back the attention to the WTP estimates, we can say that this outcome is actually not surprising. Indeed, Table 3 shows that the estimates from the 2splines-LMLM are less close to the induced value than the estimates from the other flexible distributions models. Despite this, in contrast to the second-order polynomial model, the WTP estimates from the 2splines-LMLM are still not statistically different from the induced value

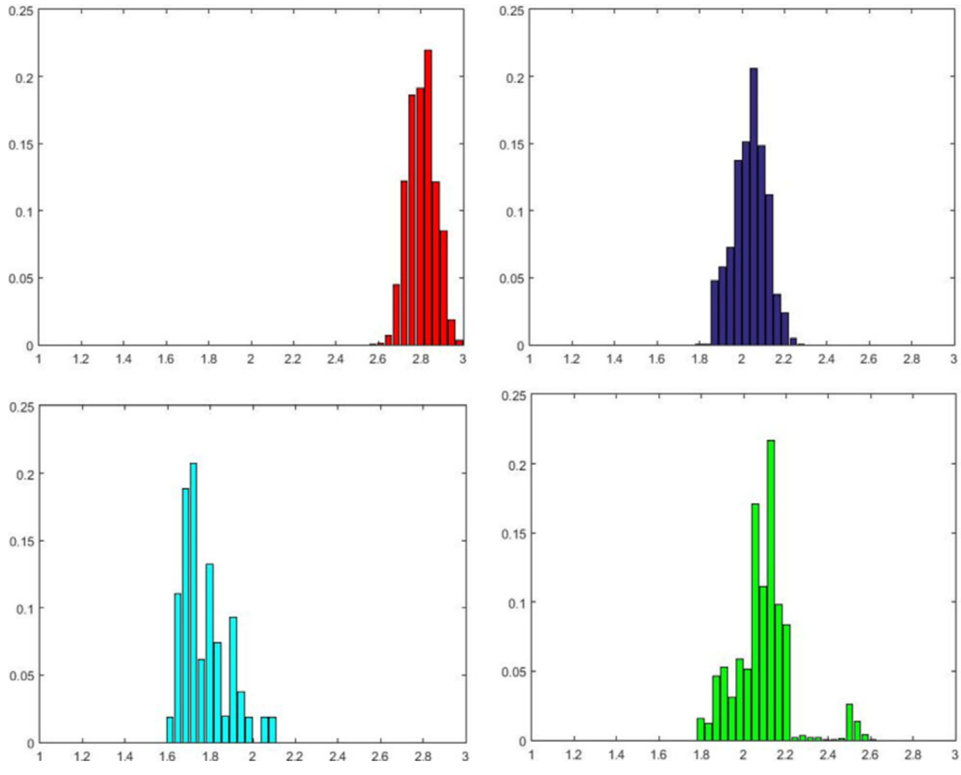

Figure 2 WTP distributions of the Shape coefficient for 2-degree polynomial (red), 4-degree polynomial (blue), 2-knots spline (cyan) and 5-step function (green). [Colour figure can be viewed at wileyonlinelibrary.com]

suggesting that estimates from 2splines-LMLM are more reliable than estimates from models where conventional distributions are assumed. This is also the case of the red colour attribute in the 5step-LMLM, since, although we do not observe homogeneity of the WTPs distributions around 2, Table 3 shows that the mean estimates of the triangle shape attribute are not statistically different from the induced value.

4. Conclusions

Our results show that similar values of WTP estimates can be obtained when using models specified in WTP space with normal and more flexible parameter distributions. This result is consistent with the studies of Train (2016) and Bansal *et al*. (2016) and Franceschinis *et al*. (2017), who used a home-grown value DCE to test model performance assuming different parameter distributions. Our study differs from these studies in that we implemented an IVCE, which allowed us to determine which model specification provided the most reliable WTP estimations. Our results indicate that the use of flexible distributions (i.e. higher order polynomials, splines and step function) can provide MWTPs for the attributes that are equal to the induced value theoretical predictions. Specifically, in our case, the fourth order provided WTP estimates that were more uniformly homogeneously distributed around the induced value.

Hence, we conclude that more reliable WTP estimates can be obtained when flexible mixing distributions are implemented. Researchers should then consider the use of this approach when estimating individuals' valuations in WTP space from DCEs. This is an important issue since WTP estimates from DCEs are not only used for business applications but also for critical welfare and policy analysis.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1 Instructions for participants