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Incorporating discontinuous preferences into the analysis of discrete choice experiments

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Abstract

Data from a discrete choice experiment on improvements of rural landscape attributes are used to investigate the implications of discontinuous preferences on willingness to pay estimates. Using a multinomial error component logit model, we explore differences in scale and unexplained variance between respondents with discontinuous and continuous preferences and condition taste intensities on whether or not each attribute was considered by the respondent during the evaluation of alternatives. Results suggest that significant improvements in model performance can be achieved when discontinuous preferences are accommodated in the econometric specification, and that the magnitude and robustness of the willingness to pay estimates are sensitive to discontinuous preferences.

Keywords

Discontinuous preferences

Heteroskedastic mixed logit

Discrete choice experiments

Multinomial error component logit model

Rural landscape

Willingness to pay

JEL Classification

C13; C15; C25; C99; Q26

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1. Introduction

Since its introduction by Louviere and Hensher (1982) and Louviere and Woodworth (1983) there have been a growing number of studies using the discrete choice experiment methodology. Discrete choice experiments are appealing as value derivation techniques because they are consistent with the Lancasterian microeconomic approach (Lancaster, 1966), whereby individuals derive utility from the different characteristics, or attributes, that a good possesses, rather than directly from the good per se. Accordingly, a change in the level of an attribute describing a given alternative may cause the respondent to favour one alternative over another that is perceived as providing an inferior combination of attributes. In discrete choice experiments, respondents are asked to select their preferred alternative from a given set (the choice set), and are typically asked to perform a sequence of such choices (Alpízar et al., 2001) giving rise to a panel of discrete choices. Experimental design theory is used to construct the alternatives, which are defined in terms of their attributes and the levels these attributes could take (Louviere et al., 2000). This type of analysis has been widely used to derive willingness to pay (*WTP*) estimates for ecological and environmental goods.

A basic assumption, which gives rise to the continuity axiom, within the discrete choice experiment framework is that of unlimited substitutability between the attributes used to succinctly describe the alternatives in the choice set. This implies that respondents make trade-offs between all attributes across each of the alternatives, and are expected to choose their most preferred alternative. Thus, the continuity axiom rules out situations where respondents focus solely on a subset of attributes, ignoring all other differences between the alternatives. Ignoring attributes in the choice set implies non-compensatory behaviour because no matter how much an attribute level is improved—if the attribute itself is ignored by the respondent—then such improvement will fail to compensate for worsening in the levels of other attributes (Spash, 2000; Rekola, 2003; Sælensminde, 2002; Lockwood, 1996). Therefore, respondents using such discontinuous preference orderings pose a problem for neoclassical analysis as they cannot be represented by a conventional utility function (Lancsar and Louviere, 2006). Without continuity, there is no trade-off between two different attributes (McIntosh and Ryan, 2002; Rosenberger et al., 2003; Gowdy and Mayumi, 2001). This is a key issue when computing the marginal rate of substitution between the attributes. While the marginal rate of substitution can be derived from the estimated parameters at the sampled population level, it is not computable for individual respondents who do not make trade-offs between the attributes. Crucially for non-market valuation, no computable relative implicit price can be computed for these respondents.

In this paper we identify respondents with discontinuous preferences on the basis of information gathered from a series of debriefing questions. Results from these questions suggest that many respondents have discontinuous preference structures when making their decisions in discrete choice experiments. The aim of this paper is to explore whether failing to account for such preferences gives rise to inappropriate model selection, poorer goodness-of-fit in discrete choice models and biased *WTP* estimates. Using multinomial error component model specifications we combine the separate approaches used by Sælensminde (2001) and Hensher et al. (2005) to examine discontinuous preferences. Firstly, as proposed in Sælensminde (2001), we allow for potential differences in scale—and error variance (heteroscedasticity)—between the subset of respondents with continuous preferences and the subset(s) of respondent with discontinuous preferences. Secondly, following Hensher et al. (2005), we adjust the weights of the attributes in estimation on the basis of whether or not the attribute was considered by the respondent. The methodology has the distinct advantage of fully incorporating both continuous and discontinuous preferences into the modelling of discrete choice. Results from the analysis provide evidence of significant improvements in goodness-of-fit and a high sensitivity of the implied *WTP* estimates when discontinuous preferences are explicitly addressed in the modelling of discrete choice. The paper uses data from a study that was used to value the benefits the general public receive from a number of rural environmental landscape improvements provided under an agri-environmental scheme in the Republic of Ireland (Campbell, 2007; Campbell et al., 2007).

The remainder of this paper is structured as follows. Section 2 reviews previous work in this area. Section 3 outlines the empirical application, the method used to identify discontinuous preferences and details the multinomial error component logit model used in the analysis. Section 4 reports the relevant results. Finally, Section 5 provides a discussion of the results and makes overall conclusions.

2. Discontinuous preferences

Continuity is based on the notion of unlimited substitutability between attributes. That is, individuals are assumed to consider—and make trade-offs—between all attributes within the choice set. However, recent survey evidence (Rosenberger et al., 2003; DeShazo and Fermo, 2002; Sælensminde, 2001; Gelso and Peterson, 2005) suggests that many respondents exhibit signs of having discontinuous preference structures. Discontinuous preferences imply non-compensatory decision-making behaviour such as lexicographic ordering and can prevent the marginal rate of substitution between attributes being estimated. In such cases, respondents have a tendency to rank alternatives solely with reference to a sub-set of attributes, ignoring all other differences between the alternatives. Such orderings can be classified according to either 'strict' lexicographic procedures—where respondents have an absolute order of preferences which precludes any degree of substitution between attributes—or 'modified' lexicographic preferences—where choice is based on thresholds and minimum levels of an attribute are necessary (Lockwood, 1996; Scott, 2002).

Respondents with discontinuous preferences are typically identified in one of two ways. The first method relies on follow-up questions. Examples of this approach have involved asking respondents whether they consider the environment should be protected irrespective of cost (Spash and Hanley, 1995), asking respondents about their 'environmental dispositions' (Rosenberger et al., 2003), and asking respondents to state the attributes they attended to during the experiment (Hensher, in press; Hensher et al., 2005). The second method of identifying discontinuous preferences inspects the actual choices made by respondents to determine whether the respondent consistently chose alternatives which were best with respect to one particular attribute. Examples of this approach include McIntosh and Ryan (2002), Sælensminde, (2001;2002) and Lockwood (1999).

Discontinuous preferences are likely to be an indication that there are some attributes within the choice set that are not behaviourally relevant to certain respondents (Sælensminde, 2006). That is, these respondents are indifferent with respect to the attributes in the choice set which they ignore. However, the literature has identified that there is a range of other factors that may give rise to discontinuous preferences in discrete choice experiments. The choice tasks respondents are expected to perform require a significant cognitive effort. Hence, respondents may be unclear how to trade one attribute against another, and this may well be exacerbated in the case of complex and unfamiliar ecological and environmental goods. Indeed, Luce et al. (2000), Blamey et al. (2002) and Caussade et al. (2005) demonstrate that a common procedure for some respondents is to consistently discriminate between the attribute(s) they perceive to be more important and those they perceive to be less important. Moreover, as presented in Heiner (1983), DeShazo and Fermo (2002), Hensher (2006) and Puckett and Hensher (in press), as choice complexity increases—identified in terms of the number of attributes, the number of choice sets, the number of levels, the ranges of the attributes and the presentation format—respondents may further restrict the range of factors that they consider and their precision in evaluation decreases. There are also a range of external factors which may explain discontinuous preferences. These are discussed in Payne et al. (1993) and Rosenberger et al. (2003) and include the cognitive ability of the respondent, the strength of attitudes, beliefs, or dispositions that the respondent holds, other demographic characteristics of the respondent, and the social and economic environment and situation (for example, distractions and time pressures during the experiment).

3. Data and methods

3.1. Data

We utilise the survey data collected and described by Campbell (2007) and Campbell et al (2007) on the general public's attitudes and preferences regarding rural environmental landscape improvements in the Republic of Ireland. The study adopted a stratified random sample to reflect the geographic distribution of the Irish adult population; the approximate rural/urban spilt; the approximate socio-economic status of the regional population; and the approximate gender and age profile of the population. In total, the questionnaire was administered by experienced interviewers to 600 respondents in 2003/4. With a further 166 potential respondents refusing to participate, the overall response rate was 78 percent.

To estimate the value of visual and ecological improvements to a number of rural environmental landscape attributes the questionnaire contained a discrete choice experiment. The rural landscape attributes concerned the conservation of Wildlife Habitats (*WH*), preservation of water quality in Rivers And Lakes (*RL*), preservation of Hedgerows (*H*) and safeguarding of Pastures (*P*) from erosion and overgrazing. Three levels were used to portray these attributes according to varying levels of landscape improvement: A Lot Of Action (*ALot*), Some Action (*Some*) and No Action (*No*). While the A Lot Of Action and Some Action levels represented a high level and an intermediate level of landscape improvement respectively, the No Action level represented the unimproved or status-quo condition. Each level of improvement was qualified by means of digitally manipulated images of landscapes to accurately represent what was achievable within the policy under valuation. The Cost attribute was specified as the value that the respondent would personally have to pay per year, through their Income Tax and Value Added Tax contributions.

The discrete choice experiment consisted of a panel of at least six repeated choice sets. Each choice set consisted of two experimentally designed alternatives—labelled 'Option A' and 'Option B'—and a status-quo alternative—labelled 'No Action'—which portrayed all the landscape attributes at the No Action level with zero cost to the respondent. The study employed a sequential experimental design with a Bayesian information structure to maximise the D_b-optimal criterion, which is outlined in Sándor and Wedel (2001). Starting from a conventional main effects fractional factorial in the first phase, a Bayesian design was employed in the second wave of sampling. The design for the final phase incorporated information from the first and second phases. For further information and an evaluation of the efficiency of the sequential experimental design approach used in this study the interested reader is directed to Scarpa et al. (2007a) and Ferrini and Scarpa (2007).

3.2. Identification of discontinuous preferences

As part of the debriefing, respondents were asked a series of questions that would help explain their thought processes and the reasons for their choice. One line of questioning focused on whether or not the respondents considered each of the attributes when making their choices during the discrete choice experiment. Respondents who did not consider all attributes were subsequently asked to indicate the attribute or attributes which they did take into account during the experiment. In this paper, respondents who considered all attributes are identified as having continuous preferences, whilst respondents who based their decisions on only a subset of attributes are identified as having discontinuous preferences.

While the incidence of respondents ignoring attributes may have arisen due to design issues or reflect coping strategies in order to deal with the cognitive burden of trading-off complex ecological and environmental goods, the development of the discrete choice experiment exercise reported here involved several rounds of design and testing to ensure that the levels of all attributes were sufficient to influence choices. This included a qualitative review of expert opinions, focus group discussions and pilot study. Therefore, we believe that respondents identified as having discontinuous preferences ignored specific attributes mainly because those attributes were truly not relevant in influencing their choices.[1]

3.3. Discrete choice model specifications

When the status-quo option is included in the set of alternatives, such inclusion can cause respondents to regard the status-quo alternative in a systematically different manner from the designed alternatives involving changes from the status-quo. This is because the status-quo is actually experienced, while the experimentally designed options are hypothetical. As a result, the utility from the experimentally designed hypothetical alternatives are more correlated amongst themselves than with the utility associated with the status-quo alternative. This may be captured by a specification with additional errors accounting for this difference in correlation across utilities. Correlation is a consequence of the fact that the experimental alternatives share this extra error component, which instead is absent from the status-quo alternative. Previous studies have found theoretical reasons for status-quo bias (Samuelson and Zeckhauser, 1988; Haaijer et al., 2001), and discrete choice experiment applications in ecological and environmental economics (see, for example, Lehtonen et al., 2003; Kontoleon and Yabe, 2003; Scarpa et al., 2005) have found these effects to be significant. To account for the fact that policy intervention takes the form of an improvement on the status-quo we employ a multinomial error component logit model specification, which allows for different patterns of correlations between utilities implying change and those referring to the status-quo (see Brownstone and Train, 1999). This approach also has the advantage of being able to compare the degree of status-quo bias and unobserved preference heterogeneity associated with the experimentally designed alternatives under each of the different models we use to investigate continuous and discontinuous preferences. The utility expressions of this approach are outlined below (we omit respondent-specific identifiers to avoid cluttering):

$$\begin{aligned} U_{Option\ A} &= \boldsymbol{\beta}'\mathbf{x} + \eta_{non\text{-}sq} + \varepsilon \\ U_{Option\ B} &= \boldsymbol{\beta}'\mathbf{x} + \eta_{non\text{-}sq} + \varepsilon \\ U_{No\ Action} &= ASC_{sq} + \boldsymbol{\beta}'\mathbf{x} + \varepsilon \end{aligned} \tag{1}$$

where, $\boldsymbol{\beta}$ is a vector of taste parameters for the attributes in the choice sets, $\mathbf{x}$; $\eta_{non\text{-}sq}$ is the error component used to induce correlation amongst the non-status-quo alternatives which is assumed to be normally distributed $\eta_{non\text{-}sq} \sim N\left(0,\sigma^2\right)$; ASC_{sq} is a non-random status-quo alternative specific constant; and, ε is the Gumbel-distributed error.[2] Note that this is analogous to the nested logit model in the sense that is allows for correlation of utilities across alternatives in the same nest, but different correlation across nests (Herriges and Phaneuf, 2002; Train, 2003; Scarpa et al. 2005). However, there is no independence of irrelevant alternatives (IIA) restriction, and ASC_{sq} captures any remaining systematic effect on the No Action alternative.

The error component can be either independent across choices or it can be the same for all choices made by the same respondent. This is relevant in discrete choice models as it breaks away from the assumption of independence in the error structure across choices made by the same respondent (Scarpa et al., 2005; 2007b). After evaluating the log-likelihood values from both specifications, we find that specifications where ε is individual-specific addressing the intrinsic correlation among observations from the same respondent outperform specifications which assume independence across choices. In this case the integrand involves a product of logit formulas, one for each respondent, rather than just one logit formula. Thus, the choice probability of observing a sequence of choices $t(n)$ from respondent n is defined in open form as:

$$P\left(t(n)\right)=\int_{\boldsymbol{\beta}}\int_{\eta}\prod_{t=1}^{t(n)}\frac{\exp\left(\lambda\left(\boldsymbol{\beta}_n'\mathbf{x}_{ti}+\eta_{in}\right)\right)}{\sum_{j\in\mathbf{A}_t}\exp\left(\lambda\left(\boldsymbol{\beta}_n'\mathbf{x}_{tj}+\eta_{jn}\right)\right)}\varphi\left(0,\sigma^2\right)\,d\eta_{jn}, \tag{2}$$

where, $\mathbf{A}_t$={*Option A*, *Option B*, *No Action*} is the choice set; λ is a scale parameter; $\varphi(\cdot)$ is the normal density; and, the value of η_j is zero when j = *No Action*. In this paper such probabilities are approximated in estimation by simulating the log-likelihood with 1,000 Halton draws. For further details on Halton sequences see Bhat (2001) and Train (2003).

In this paper we test whether or not the variation of the unobserved effects—or error variance heterogeneity—of the subset of respondents with discontinuous preferences is similar to that of the subset of respondents with continuous preferences. This is examined by specifying different scale parameters for the two subsets. In practice this is achieved by arbitrarily normalising the scale of the subset of respondents with continuous preferences, λ_{cont}, to one, whilst allowing the scale parameter of the subset of respondents with discontinuous preferences, $\lambda_{discont}$, to vary. This is similar to a number of studies which have specified separate scale factors to test for the effects of learning, fatigue, complexity and consistency (see, for example, Sælensminde, 2001; Breffle and Rowe, 2002; Dellaert et al., 1999; Carlsson and Martinsson, 2001). Unlike these studies, however, where the logit scaling is implemented using either one-dimensional grid-search procedures to literally graph the log-likelihood function (see Swait and Louviere, 1993) or artificial nested tree structures (see Hensher and Bradley, 1993), in this paper we explicitly include the scale parameter in the model and estimate it by full information maximum likelihood, thereby obtaining efficient estimates. Each utility function corresponding to respondents with discontinuous preferences is multiplied by $\lambda_{discont}$. This approach effectively treats all respondents with discontinuous preferences as homogenous. However, it is conceivable that groups of respondents who adopted a particular attribute processing rule may have a different error variance than a group of respondents who adopted another attribute processing rule. To test this we introduce a further model with five scale factors—one for each of our exogenously defined attribute processing rules. In this paper we define the attribute processing rules on the basis of the number of attributes respondents stated they ignored while making their choices. These scale parameters are labelled $\lambda_{discont\_n}$, where n={1, 2, 3, 4} to denote the number of attributes ignored. Again, the scale of the subset of respondents with continuous preferences (that is, respondents who did not ignore any attributes), λ_{cont}, is normalised to one.

Overlooking the fact that some respondents did not trade-off the levels of one attribute against another attribute will lead to biased estimates of the average level of the parameter in the population. To accommodate discontinuous preferences and to ensure that unnecessary weight is not placed on the attributes ignored by respondents, we thus compare models where the attribute parameters are specified as a function of a dummy variable representing whether or not the attribute was considered by the respondent. Following Hensher et al. (2005), for these models the choice probabilities are constructed in such a way that the actual elements of $\boldsymbol{\beta}_n$ that enter the likelihood function are set to zero in cases where the element is associated with an attribute ignored by respondent n. While respondents may have ignored specific attributes because they had zero marginal (dis)utilities—and thus zero *WTP*—for these attributes, it should be noted, however, that under this specification we are not arguing that the respondent's actual marginal (dis)utility for attributes which they did not trade-off is zero. Rather, under this speciation we account for the fact that the levels of the attributes which were ignored did not influence their choice—which is not necessarily the same thing as having a zero preference for that attribute. For instance, it is unlikely that a respondent who ignored the Cost attribute has a zero marginal disutility of cost—that is, *ceteris paribus*, they are almost always likely to prefer cheaper goods to more expensive goods. But the levels of the Cost attribute did not influence the respondent's choices in the discrete choice experiment and, thus, the actual choice set is different for this respondent.

4. Results

4.1. Incidence of discontinuous preferences

Of the 600 respondents, 36 did not provide answers to the debriefing questions and have, therefore, been removed from the analysis. The attributes or combinations of attributes considered by the remaining 564 respondents during the discrete choice experiment are reported in Table 1. As may be seen, 361 (64 percent) respondents considered all attributes in the discrete choice experiment and are, therefore, identified as having continuous preferences. The remaining 203 (36 percent) respondents are considered to have discontinuous preferences.

Further inspection of Table 1 reveals that out of the 564 respondents, 61 (11 percent) respondents focused solely on the Rivers And Lakes attribute. Collectively, 48 (9 percent) respondents focused solely on one of the remaining attributes. Hence around one-fifth of respondents considered only one attribute in the discrete choice experiment, thus providing no information on their willingness to make trade-offs among the attributes. When reaching their decisions in the discrete choice experiment 60 (11 percent) respondents took into account two attributes. Three and four attributes were considered by 27 (5 percent) and seven (1 percent) respondents respectively.

Overall, the Rivers And Lakes attribute was considered by 500 (89 percent) respondents. While we accept that this high proportion may have been partially due to some respondents treating the Rivers And Lakes attribute as an important indicator of the overall state of the environment and/or associating it with the quality of drinking water, evidence from the focus group discussions and pilot study clearly identified that it is most likely due to the general public's strong preference for aesthetic and ecological improvements concerning rivers and lakes. The Wildlife Habitats, Pastures and Hedgerows attributes were taken into account in the discrete choice experiment by 437 (77 percent), 416 (74 percent) and 399 (71 percent) respondents respectively. The Cost attribute was considered by 391 (69 percent) respondents. Accordingly, the Cost attribute was the attribute least taken into account in the discrete choice experiment which is an important finding in a study that is primarily concerned with deriving *WTP* estimates. This result would suggest that the Cost attribute was the least relevant factor in influencing the respondent's choices. In other words, many respondents wanted rural environmental landscape improvements irrespective of the costs involved. Evidence presented in Puckett and Hensher (in press) would also suggest that the range and relative equivalence of the Cost attribute levels among alternatives in a particular choice set may have led respondents to ignore the Cost attribute in some choice sets but not in others. Further scrutiny of Table 1 reveals that only 377 (67 percent) made trade-offs between the Cost attribute and at least one rural environmental landscape attribute.

4.2. Estimation results

Reported in Table 2 are the parameter estimates for six models, all of which were estimated in BIOGEME (Bierlaire 2003). Model 1 pertains to the estimation of the discrete choice experiment without accounting for the fact that some respondents exhibited discontinuous preferences. Model 2 allows for differences in scale between the subset of respondents identified as having continuous preferences and the subset identified as having discontinuous preferences. Model 3 encompasses separate scale parameters for subsets of respondents who ignored a different number of attributes. In Model 4 the attribute parameters are specified as a function of a dummy variable representing whether or not the attribute was considered by the respondent. Model 5 allows for differences in scale and the attribute parameters are multiplied by a dummy variable denoting whether or not the attribute was considered. In Model 6 the attribute parameters are also a function of whether the attribute was considered by the respondent and also allows for differences in scale between subsets of respondents based on the attribute processing rule they adopted. The total number of observations used in model estimation is 4,036.

All models are found to be statistically significant and have acceptable ρ^2 values. Moreover, as reflected by the increases in the log-likelihood function ($\mathcal{L}$) and ρ^2 and reduction in the Akaike information criterion (AIC) Bayesian information criterion (BIC) statistics, there is an overall increase in model performance as one moves from Model 1 to Model 6. In all six models the parameter estimates for the rural environmental landscape attributes are statistically significant, with positive signs—implying that respondents, all else held constant, prefer rural environmental landscapes to be in an improved condition. Notice also, that the relative dimensions of these parameters correspond with theoretical expectations of decreasing marginal utility. In all models, the *Cost* parameter is significant and in line with a priori expectations. The fact that ASC_{sq} is found to be negative and significant in all models indicates that there is some degree of status-quo bias—ceteris paribus, the respondents found the No Action alternative less desirable than the experimentally designed alternatives. For all models the error component, $\eta_{non\text{-}sq}$, is found to be significantly different from zero, which insinuates heterogeneity across respondents in their intensities of tastes for the Option A and Option B alternatives.

Comparison of the AIC and BIC statistics obtained under Model 2 vis-à-vis Model 1 and Model 5 vis-à-vis Model 4, indicates an improvement in model performance even after accounting for the loss of parsimony caused by the estimation of an addition parameter, $\lambda_{discont}$, to allow for differences in scale between the respondent we identified as having continuous preferences and those we identified as having discontinuous preferences. Similarly, inspection of the AIC and BIC statistics attained under Models 3 and 6 suggests that model performance can be further enhanced by including scale factors to denote subsets of respondents who adopt different attribute processing rules. To formally test for improvements in modelling performance we conduct likelihood ratio tests. This statistic is given by equation (3) (Swait and Louviere, 1993).

$$-2\left(\mathcal{L}\left(\hat{\boldsymbol{\beta}}_R\right)-\mathcal{L}\left(\hat{\boldsymbol{\beta}}_U\right)\right), \tag{3}$$

where, $\hat{\boldsymbol{\beta}}_R$ denotes the estimated parameters of the restricted model; and, $\hat{\boldsymbol{\beta}}_U$ denotes the parameter estimates of the unrestricted model. The test is asymptotically χ^2 distributed with k degrees of freedom, where k is the number of additional parameters used in computing $\mathcal{L}\left(\hat{\boldsymbol{\beta}}_U\right)$. With test statistics of 22.34 and 142.62 for Model 1 versus Model 2 and Model 4 versus Model 5 respectively, against a χ^2 critical value of 3.84 ($\chi^2_{1,0.05}$), we can reject the null hypothesis that there is no significant difference in scale between the subset of respondents with continuous preferences and the subset of respondents with discontinuous preferences. Not surprisingly, in both Model 2 and Model 5 the scale parameters are found to be significantly different (that is, $\lambda_{cont} \neq \lambda_{discont}$). Likelihood ratio tests for Model 2 versus Model

3 and Model 5 versus Model 6 of 13.94 and 30.42 respectively, against a χ^2 critical value of 7.82 ($\chi^2_{3,0.05}$), confirm that improvements in goodness-of-fit can be achieved by allowing for different error variances among subsets who ignore a different number of attributes. In addition, in Models 3 and 6 we find that the scale parameter associated with the subset of respondents with continuous preferences is significantly different to scale parameters associated with the subsets of respondents who ignored attributes. Given that these scale parameters are inversely related to the variance of the error term—recall $\sigma^2 = \pi^2 / 6\lambda^2$, where σ^2 is the variance of the error term—implies that the higher the scale, the smaller the variance. Therefore, the relative variance between the subsets of respondents is:

$$\frac{\sigma^2_{discont(\_n)}}{\sigma^2_{cont}} = \frac{\pi^2 / 6\lambda^2_{discont(\_n)}}{\pi^2 / 6\lambda^2_{cont}} = \frac{\lambda^2_{discont(\_n)}}{\lambda^2_{cont}} = \left(\frac{\lambda_{discont(\_n)}}{\lambda_{cont}}\right)^2 . \tag{4}$$

Substituting in the scale parameters obtained under Models 2 and 5 we find that the variance of the subset of respondents with discontinuous preferences was over twice as high under Model 2 and over six times higher under Model 5 compared to the subset of respondents with continuous preferences. Relative to respondents with continuous preferences, the variance of the subset of respondents who ignored one attribute is found to be 16 times higher in Model 3 and around 26 times higher in Model 6. In both Models 3 and 6 the variance of respondents who ignored two attributes is found to be over three times higher than respondents with continuous preferences. The variance for the subset of respondents who ignored three attributes is found to be almost twice as high under Model 3 and over three times higher under Model 6. Respondents who only considered one attribute are found to have almost twice as much variance in Model 3 and around ten times higher variance in Model 6 than respondents who considered all attributes.

Since the models in which the attributes are specified as a function of whether or not they were considered have the same number of parameters as the models which do not specify the attributes in anyway, the best fitting model is simply the one with the highest log-likelihood. Accordingly, Models 4, 5 and 6 are found to outperform their equivalent specification which does not accommodate discontinuous preferences, that is, Models 1, 2 and 3 respectively.

4.3. WTP and implications of discontinuous preferences

An alternative way of teasing out the effect of axiomatic violations of compensatory decision-making, which is likely to be of greater interest to policy makers, is to consider the effects on the *WTP* estimates. Table 3 reports the marginal *WTP* estimates derived under Models 1 to 6—which are obtained by dividing the parameters of the rural landscape attributes by the associated Cost parameter. Importantly, the *WTP* estimates are all statistically significant and the implied monotonicity in the magnitude of *WTP* for the two levels of action is adequately reflected for all attributes. The magnitudes of the *WTP* estimates are also in line with those reported in recent studies. As may be seen, we find that the implied preference ordering remained relatively consistent across the models—highest *WTP* values are found for preserving Rivers And Lakes, lowest for maintenance of Hedgerows, with safeguarding Wildlife Habitats and Pastures ranking in between. Assessment of the implied preference orderings also dispenses with the idea that respondents focused solely on a subset of attributes as a form of protest voting behaviour, as highest *WTP* estimates are attached to the rural environmental landscape improvements which were concentrated on most in the discrete choice experiment, namely those concerning Rivers And Lakes.

Inspection of Table 3 shows that the *WTP* estimates derived under the six model specifications vary substantially. In the main—as reflected by the average *WTP* estimates—there appears to be a general shift downwards in the magnitude of *WTP* as one moves from the estimates obtained under Model 1 to those under Model 6. Indeed, on average the *WTP* estimate derived under Model 6 is 57 percent lower than that obtained under Model 1. To confirm this observation and to assess the statistical significance of the differences in *WTP*, we gauge the equality of the estimates with the following asymptotically normal test statistic:

$$\frac{\widehat{WTP}_k^1 - \widehat{WTP}_k^2}{\sqrt{Var\left(\widehat{WTP}_k^1\right) - Var\left(\widehat{WTP}_k^2\right)}}, \tag{5}$$

where WTP_k is the parameter of the *K*th attribute; $\widehat{WTP}_k^1$ is the estimate of WTP_k from Model 1; and, $\widehat{WTP}_k^2$ is the estimate of WTP_k from Model 2. Results of this test are reported in Table **4**. As the results indicate, with the exception of A Lot Of Action for Wildlife Habitats, there is no significant difference between the *WTP* values derived under Models 1, 2 and 3—implying that simply allowing for differences in scale between respondents with continuous and discontinuous generally does not affect the magnitudes of the *WTP* estimates.

In the main, the *WTP* estimates derived under Models 4, 5 and 6 are found to be significantly lower than those obtained from Model 1, 2 and 3 respectively—indicating that conditioning the taste intensities on whether or not the attributes are considered leads to a reduction in the magnitude of *WTP*. In contrast to Models 1, 2 and 3, where specifying different scale parameters for respondents with discontinuous preferences did not affect *WTP*, in Models 4, 5 and 6 we generally observe significant reductions in *WTP*. Therefore, accommodating different scale parameters and specifying the attributes as dummy variables to denote whether or not they were considered leads to a decline in *WTP*. However, no statistical difference is detected between the *WTP* estimates obtained under Models 5 and 6. As a result, disaggregating the discontinuous scale parameter into four scale parameters—one for each attribute processing rule—does not have any effect on the magnitude of the *WTP* estimates.

Further scrutiny of Table 3 also reveals that the *WTP* values are generally approximated with much greater precision as one moves from the estimates obtained under Model 1 to those derived under Model 6. In fact, relative to Model 6 the signal-to-noise ratio of the average *WTP* estimate is 56 percent lower (1-10.2/23.5) for Model 1, 55 percent lower for Model 2, 55 percent lower for Model 3, 37 percent lower for Model 4 and 9 percent lower for Model 5. Thus, allowing for differences in scale between the subset of respondents with discontinuous preferences and the subset of respondents with continuous preferences and specifying the attribute parameters as a function of whether or not they were considered provides *WTP* estimates which are significantly lower and statistically more robust. This result is consistent with previous stated preference studies.

5. Discussion and conclusion

The study was designed to provide straightforward insight into preferences between four rural environmental landscape attributes and, as addressed in this paper, the implications of discontinuous preferences. Scrutiny of responses to follow-up questions identified that many respondents made choices based solely on their most preferred attribute(s). Crucially for a valuation study, the Cost attribute was the attribute least attended to in the discrete choice experiment. This was an important discovery, as respondents who do not make trade-offs between landscape quality and cost do not have a relative price and no tangency with the production frontier. This is also a somewhat worrying finding in that it provides evidence that welfare estimates derived using the discrete choice experiment methodology may be misrepresented unless they allow for the fact that the monetary attribute may not have been considered.

From a modelling point of view, parameters obtained from models which fail to take into account discontinuous preferences are found to be erroneous and biased. Results in this paper reveal that the error variance of the subset of respondents who exhibited discontinuous preference structures was up to six times higher than the subset of respondents with continuous preference structures. Moreover, when this subset of discontinuous respondents was further disaggregated into subsets of respondents who adopted different attribute processing rules we find that the error variance for some subsets of respondents was up to 26 times higher than respondents with continuous preferences. As a result, significant improvements in model performance and, thus, more accurate utility expressions are achieved when the modelling considers the difference in scale between respondents with continuous preferences and those with discontinuous preferences. Similarly, specifying the attribute parameters as a function of a dummy variable representing whether or not the attribute was considered by the respondent leads to significant improvements in model performance. Importantly, the fact that a significant proportion of respondents are found to have discontinuous preferences, combined with the reported effect that accommodating such preferences results in a substantial lowering in the magnitude of the *WTP* estimates—on average, of the order of almost 60 percent between the basic model and the most informed model—suggests some caution when this issue is neglected in deriving non-market valuation estimates by means of the discrete choice experiment methodology. Moreover, the precision of the *WTP* estimates is also greatly enhanced when discontinuous preferences are taken into consideration.

Since results from this study and other valuation studies are used to inform policy decisions, failing to take into account discontinuous preferences could have profound policy repercussions in that the allocation of resources may not reflect the true benefits. The evidence presented in this paper quite clearly suggests that discrete choice experiment studies should incorporate procedures for identifying and dealing with discontinuous preferences.

Notes

1. We point out that we treat the exogenously defined discontinuity of preferences as deterministic. We, therefore, assume that the combination of attributes which each respondent stated they considered accurately reflects the attributes they actually did consider while making their choices. See Hensher et al. (2007) for an analysis which relaxes the deterministic assumption by treating the attribute processing rules in a stochastic manner.
2. Tests for additional random parameters did not improve on the results obtained from the multinomial error component models. Therefore, our preferred model does not include any other random parameters apart from the error component, $\eta_{non\text{-}sq}$.

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Table 1 Attributes and combinations of attributes taken into account by the respondents during the discrete choice experiment

Attributes and combinations of attributes taken into account	Number	Percent
Wildlife Habitats, Rivers And Lakes, Hedgerows, Pastures and Cost	361	64.01
Wildlife Habitats, Rivers And Lakes, Hedgerows and Pastures	6	1.06
Wildlife Habitats, Rivers And Lakes, Hedgerows and Cost	1	0.18
Wildlife Habitats, Rivers And Lakes and Hedgerows	14	2.48
Wildlife Habitats, Rivers And Lakes and Pastures	3	0.53
Wildlife Habitats, Rivers And Lakes and Cost	3	0.53
Rivers And Lakes, Hedgerows and Pastures	2	0.35
Rivers And Lakes, Hedgerows and Cost	2	0.35
Rivers And Lakes, Pastures and Cost	1	0.18
Hedgerows, Pastures and Cost	2	0.35
Wildlife Habitats and Rivers And Lakes	26	4.61
Wildlife Habitats and Hedgerows	2	0.35
Wildlife Habitats and Pastures	6	1.06
Wildlife Habitats and Cost	1	0.18
Rivers And Lakes and Hedgerows	5	0.89
Rivers And Lakes and Pastures	12	2.13
Rivers And Lakes and Cost	3	0.53
Hedgerows and Pastures	2	0.35
Pastures and Cost	3	0.53
Wildlife Habitats	14	2.48
Rivers And Lakes	61	10.82
Hedgerows	2	0.35
Pastures	18	3.19
Cost	14	2.48
Total	**564**	**100.00**

Table 2 Multinomial error component logit model results

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	beta	*t*-ratio	beta	*t*-ratio	beta	*t*-ratio	beta	*t*-ratio	beta	*t*-ratio	beta	*t*-ratio
WH_ALot	0.579	10.6	0.525	10.6	0.537	10.8	0.603	9.8	0.512	10.6	0.522	10.7
WH_Some	0.378	5.8	0.366	6.4	0.377	6.6	0.336	4.7	0.256	4.9	0.289	5.5
RL_ALot	1.347	21.8	1.194	18.1	1.188	18.0	1.501	23.0	1.093	16.7	1.100	16.9
RL_Some	0.837	11.6	0.757	11.3	0.739	11.1	0.863	12.1	0.600	11.0	0.605	11.1
H_ALot	0.360	6.3	0.304	5.9	0.321	6.2	0.474	6.9	0.375	6.6	0.408	7.0
H_Some	0.157	2.6	0.132	2.5	0.139	2.7	0.197	2.8	0.124	2.2	0.153	2.6
P_ALot	0.598	10.3	0.548	10.4	0.533	10.3	0.668	10.1	0.576	10.9	0.548	10.5
P_Some	0.551	8.6	0.510	8.9	0.515	9.0	0.614	8.6	0.502	9.1	0.473	8.7
Cost	-0.003	-3.2	-0.002	-3.0	-0.002	-3.0	-0.005	-4.8	-0.006	-6.2	-0.006	-6.5
ASC_{sq}	-4.375	-7.6	-3.978	-7.6	-3.989	-7.6	-4.737	-8.3	-3.711	-8.1	-3.717	-8.1
$\eta_{non\text{-}sq}$	2.891	7.9	2.643	8.0	2.644	7.9	2.940	7.9	2.241	7.7	2.254	7.8
λ_{cont}			1.000	Fixed	1.000	Fixed			1.000	Fixed	1.000	Fixed
$\lambda_{discont}$			1.424	4.0[a]					2.459	8.0[a]		
$\lambda_{discont\_1}$					3.984	2.5[a]					5.122	2.3[a]
$\lambda_{discont\_2}$					1.770	2.8[a]					1.849	3.0[a]
$\lambda_{discont\_3}$					1.403	2.5[a]					1.866	4.2[a]
$\lambda_{discont\_4}$					1.293	2.4[a]					3.188	8.0[a]
$\mathcal{L}$	-2,673		-2,662		-2,656		-2,626		-2,555		-2,540	
χ^2	3,522[b]		3,544[c]		3,558[d]		3,615[b]		3,758[c]		3,788[d]	
ρ^2	0.397		0.400		0.401		0.408		0.424		0.427	
AIC	1.330		1.325		1.323		1.307		1.272		1.266	
BIC	1.347		1.344		1.346		1.324		1.291		1.289	

[a] *t*-ratio w.r.t. 1.

[b] critical value equal to 19.68 ($\chi^2_{11,0.05}$).

[c] critical value equal to 21.03 ($\chi^2_{12,0.05}$).

[d] critical value equal to 25.00 ($\chi^2_{15,0.05}$).

Table 3 Willingness to pay estimates (€/year)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	beta	*t*-ratio	beta	*t*-ratio	beta	*t*-ratio	beta	*t*-ratio	beta	*t*-ratio	beta	*t*-ratio
WH_ALot	200.26	28.0	222.97	38.0	226.05	25.2	116.02	25.1	92.15	24.2	92.14	24.3
WH_Some	130.80	9.4	155.71	10.5	158.54	10.9	64.54	12.9	46.01	27.5	50.99	25.8
RL_ALot	465.87	31.8	507.37	22.9	500.20	22.7	288.68	36.8	196.61	34.6	193.93	29.7
RL_Some	289.37	10.0	321.63	10.7	311.23	10.7	166.06	17.5	107.95	38.0	106.66	89.7
H_ALot	124.63	6.6	128.98	6.6	134.98	7.0	91.23	9.7	67.53	13.2	71.92	15.2
H_Some	54.14	4.3	55.98	4.2	58.55	4.4	37.84	6.4	22.38	7.9	26.93	9.4
P_ALot	206.75	9.4	232.99	10.4	224.39	9.8	128.40	13.2	103.60	23.0	96.60	27.7
P_Some	190.59	8.3	216.54	8.6	216.64	8.6	118.10	13.2	90.28	22.6	83.46	28.5
Average	**207.80**	**10.2**	**230.27**	**10.5**	**228.82**	**10.6**	**126.36**	**14.8**	**90.81**	**21.4**	**90.33**	**23.5**

Table 4 Tests for equality of willingness to pay estimates

	Model 1 vs. Model 2	Model 1 vs. Model 3	Model 1 vs. Model 4	Model 1 vs. Model 5	Model 1 vs. Model 6	Model 2 vs. Model 3	Model 2 vs. Model 4	Model 2 vs. Model 5	Model 2 vs. Model 6	Model 3 vs. Model 4	Model 3 vs. Model 5	Model 3 vs. Model 6	Model 4 vs. Model 5	Model 4 vs. Model 6	Model 5 vs. Model 6
WH_ALot	-2.46	-2.25	9.89	13.34	13.36	-0.29	14.33	18.70	18.74	10.90	13.72	13.74	3.98	4.00	0.00
WH_Some	-1.23	-1.38	4.49	6.07	5.69	-0.14	5.83	7.36	7.01	6.13	7.71	7.35	3.52	2.52	-1.92
RL_ALot	-1.56	-1.30	10.67	17.14	16.96	0.23	9.31	13.60	13.58	9.04	13.34	13.32	9.51	9.28	0.31
RL_Some	-0.77	-0.53	4.03	6.21	6.28	0.25	4.92	7.06	7.13	4.74	6.95	7.02	5.86	6.20	0.42
H_ALot	-0.16	-0.38	1.58	2.91	2.70	-0.22	1.75	3.06	2.86	2.04	3.38	3.18	2.22	1.84	-0.63
H_Some	-0.10	-0.24	1.18	2.48	2.12	-0.14	1.24	2.44	2.11	1.42	2.65	2.31	2.37	1.67	-1.12
P_ALot	-0.83	-0.56	3.26	4.60	4.95	0.27	4.27	5.64	5.99	3.86	5.18	5.52	2.31	3.07	1.23
P_Some	-0.76	-0.77	2.95	4.33	4.65	0.00	3.67	4.93	5.23	3.68	4.95	5.25	2.84	3.68	1.38
Average	**-0.75**	**-0.71**	**3.69**	**5.63**	**5.67**	**0.05**	**4.42**	**6.26**	**6.30**	**4.40**	**6.24**	**6.29**	**3.73**	**3.84**	**0.08**