Combining mixed logit models and random effects models to identify the determinants of willingness to pay for rural landscape improvements

Danny CAMPBELL

Gibson Institute for Land, Food and Environment, Queen's University Belfast, N. Ireland

(d.campbell@qub.ac.uk)

Paper written for the Agricultural Economics Society 81st Annual Conference

Reading, March 2006

Abstract

This paper reports the findings from a discrete choice experiment study designed to estimate the economic benefits associated with rural landscape improvements in Ireland. Using a mixed logit model, the panel nature of the dataset is exploited to retrieve willingness to pay values for every individual in the sample. This departs from customary approaches in which the willingness to pay estimates are normally expressed as measures of central tendency of an a priori distribution. In a different vein from analysis conducted in previous discrete choice experiment studies, this paper uses random effects models for panel data to identify the determinants of the individual-specific willingness to pay estimates. In comparison with the standard methods used to incorporate individual-specific variables into the analysis of discrete choice experiments, the analytical approach outlined in this paper is shown to add considerably more validity and explanatory power to welfare estimates.

Keywords: *Agri-environment; discrete choice experiments; mixed logit; panel data; random effects; willingness to pay.*

JEL classifications: *C33, C35, Q24, Q51.*

1. Introduction

After more than fifty years of European agricultural policies designed to support farm incomes via farm commodity prices, there has been a significant shift in emphasis to area-based payments and payments for the supply of environmental goods, or 'green payments'. Such agri-environmental schemes have become an important component within the Common Agricultural Policy (CAP). In particular, the Rural Environment Protection (REP) Scheme was introduced in Ireland in 1994, and designed to pay farmers for carrying out their farming activities in an environmentally friendly manner and improve the broadly defined rural environment, and the rural landscape. Agri-environmental policy in Ireland is also of interest in that it is unique in the European Union in the combination of its comprehensiveness and its being available to all farmers throughout the country (Emerson and Gillmor, 1999). With this in mind, a key objective of this paper is to quantify the benefits arising from such a comprehensive and universal policy. Specifically, reported in this paper are the results from a public survey that was carried out to address the value of the major farm landscape improvement measures within the REP Scheme in Ireland.

The policy measures of the REP Scheme contribute to various rural landscape attributes, and hence a multi-attribute valuation approach is warranted. At the same time, the public good and non-market nature of rural landscapes favour the use of a stated preference methodology employed for the estimation of existence benefits. This poses a number of methodological issues, yet to be satisfactorily addressed in the literature. In particular, a discrete choice experiment survey instrument was developed which was centred around digital images which were selected to represent rural landscape improvement measures under the REP Scheme. Further, given the national scope of this study, and like in many similar studies which rely on expensive face-to-face interviewing, sample size was an issue. Hence, efficiency gains were sought and achieved by adopting, for the first time in the public good valuation literature, a sequential experimental design with Bayesian updating.

Previous research demonstrated that there are a number attributes of the individual which influence willingness to pay (WTP) for rural landscape features (see, for example, Schläpfer and Hanley, 2003). However, in discrete choice experiments while attributes of the good under evaluation generally vary across alternatives, attributes of the individual remain the same across all alternatives and thus cannot enter directly into the model on their own, as they would drop out from the estimation. In an econometric sense this means that the effect of individual characteristics are not identifiable in the probability of choosing specific alternatives, with the result that model parameters (that is, the indirect utility function) are the same for each sampled individual. They can only enter the model if they are specified such that they create differences in utility over alternatives. Attributes of the individuals must, therefore, be interacted either with the choice-specific attributes or with the alternative specific constants (Hanley *et al.*, 2001). However, neither of these methods provide an entirely suitable means of identifying the determinants of WTP. This is because they indicate the effect of the individual characteristic on the utility associated with a choice-specific attribute or an alternative and not the effect on WTP *per se*.

This paper proposes an alternative means of identifying the determinants of WTP. The approach outlined in this paper combines mixed logit models and random effects models. This is achieved by first exploiting the panel nature of the discrete choice experiment dataset using a mixed logit specification to retrieve the distribution of part-worths (WTP values) for the individual in the sample, conditional on the individual sequence of observed choices in the discrete choice experiment. This departs from customary approaches in which the WTP estimates are normally expressed as measures of central tendency of an *a priori* distribution, such as mean or median value estimates with their computed standard errors. Instead, the distributions of these values estimated for each individual are compared and contrasted for a number of rural landscape improvements. Moreover, since benefit estimates for strict improvements impose conceptual lower bounds on values which may be estimated in different ways, the occurrence of negative values in inference must therefore be excluded by making adequate assumptions in model specification and estimation. In this paper, estimates are bound such that they are strictly positive while allowing for preference variation within the sample. Subsequently, the individual-specific WTP estimates for each of the rural landscape improvements are pooled to enable the exploration of the inter-individual differences and intra-individual dynamics of WTP. Since ignoring the panel structure of this pooled dataset would result in understated standard errors and the use of ordinary least squares as an estimation method would not provide efficient estimates of the regression coefficients (Wooldridge, 2002), models for panel data model are hence constructed to model the determinants of WTP. Specifically, due to the fact that WTP is hypothesised to be affected by regressors which are invariant across panels, such as the socio-demographic characteristics, a random effects specification is used. Moreover, the use of a random rather than a fixed effect model is preferable if the sampled individuals are believed to be drawn from a larger population (Greene, 2003). It would appear that this is the first paper which combines mixed logit models and random effects models. In this respect, this is a novel contribution to the literature on the valuation of environmental and natural resources using discrete choice experiments. Evidence in this paper shows that it provides a very suitable means of examining the WTP estimates derived from discrete choice experiments. Crucially, the empirical method of this paper lends perfectly to the information content of the data collected in most discrete choice experiment studies.

The remainder of the paper is structured as follows. Section 2 details the empirical example presented in this paper. The empirical application is used to demonstrate the benefits of combining discrete choice models and panel data models, rather than to discuss the discrete choice experiment methodology or panel data models in detail. A complete overview of these are methodologies are thus beyond the scope of this paper. Instead, readers unfamiliar with discrete choice experiments are referred to Louviere *et al.* (2003) and Hensher *et al.* (2005a) and references cited therein. Similarly, readers unfamiliar with panel data model are directed to Nerlove (2002), Wooldridge (2002) and Hsiao (2003) for a complete overview. However, for the benefit of readers not so familiar with the mixed logit model and random effects model, these are thoroughly outlined in Section 3. This includes the econometric specifications used in this paper. Section 4 develops the empirical analyses and discusses the results obtained. Finally, the main conclusions and recommendations are presented in Section 5.

2. Survey design

2.1. Discrete choice experiment

The discrete choice experiment exercises reported here involved several rounds of design and testing. This process began with a qualitative review of expert opinions. Having identified the policy relevant attributes, further qualitative research was carried out to refine the definitions of these attributes so they could be used in the survey. This was achieved through a series of focus group discussions with members of the public. Following the focus group discussions pilot testing of the survey instrument was conducted in the field. This allowed the collection of additional information, which along with expert judgment and observations from the focus group discussions, was used to identify and refine the attributes and their levels.

In the final version of the survey a total of eight important landscape attributes were identified. Evidence from the focus group discussion, however, revealed that respondents had difficulty evaluating choice tasks with more than five attributes. To circumvent this, the survey contained two separate discrete choice experiments, each comprised of four rural landscape attributes. To avoid any biases that might exist due to the ordering of the discrete choice experiments, two versions of each questionnaire were developed, each version presenting the two discrete choice experiments in a different sequence. This paper reports the results from one of these discrete choice experiments, which is sufficient to address the methodological issues at stake. The four rural landscape improvements focused on in this paper are the protection of mountain land from overstocking, enhancement of the visual aspect of stonewalls, farmyards and farm heritage buildings. Three levels were used to depict each of these landscape attributes according to the level of action made to conserve or enhance the attribute. To minimise respondent confusion the levels for each landscape attribute was denoted using the same labels: a lot of action, some action and no action. While the a lot of action and some action levels represented a high level and an intermediate level of improvement respectively, the no action level represented the unimproved or status-quo condition.

Since valuation of landscape components is very subjective, and verbal descriptions can be interpreted differently on the basis of individual experience, each level of improvement was qualified by means of digitally manipulated images of landscapes to accurately represent what is achievable within the policy under valuation. This involved the manipulation of a 'control' photograph to depict either more of or less of the attribute in question. This method was used so that on the one hand the changes in the attribute levels could be easily identified while holding other features of the landscape constant. On the other hand the respondent would not perceive as ostensibly unrealistic the computer generated landscape illustrations. Different stocking densities in an upland area reflecting overgrazing and soil erosion were used to depict the mountain land attribute. The stonewalls attribute illustrated the consequence that their condition and their removal has on the appearance of the countryside. Similarly, the farmyard tidiness attribute portrayed a farmyard at different states of tidiness and the cultural heritage attribute showed the impact that different management practices have on old farm buildings and historical features. All images and accompanying text were tested in the focus group discussions and pilot study to ensure a satisfactory understanding and scenario acceptance by respondents.

To enable the estimation of welfare values the discrete choice experiment also contained a cost attribute. This was described as the expected annual cost of implementing the alternatives represented in the choice tasks. This 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, to implement the alternative. As discussed later a sequential experimental design was employed which enabled the levels of the monetary attribute to be adjusted in response to the preliminary findings following each phase of the survey.

The discrete choice experiment required respondents to indicate their preferred alternative in a panel of at least six repeated choice tasks. Each choice task 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 (see Figure 1). When making their choices, respondents were asked to consider that the policy options relating to rural landscape improvements were restricted to only the three alternatives. Respondents were also reminded to take into account whether they thought the rural landscape improvements were worth it.

2.2. Experimental design

Since different experimental designs can significantly influence the accuracy of WTP estimates (Lusk and Norwood, 2005), it is important to use an experimental design that minimises an efficiency criterion. Given the national scope of this study, and the cost of face-to-face surveys of this kind, sample size was also an issue. To increase sampling efficiency a sequential experimental design with a Bayesian information structure was employed (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. However, not all values of the attributes were allocated in the design by this approach. The numerical values of the cost attribute were assigned on the basis of realism so as to balance the probabilities of choices across alternatives in the choice task (Kanninen, 2002). Significantly, adapting the sequential experimental design was found to have increased sampling efficiency by 44 percent and reduced survey costs by 30 percent (see Campbell, 2006). For further information and an evaluation of the efficiency of the sequential experimental design approach used in this study the reader is referred to Ferrini and Scarpa (forthcoming) and Scarpa *et al*. (2005).

2.3. Sampling frame

In order to achieve a spatially representative sample of the general public within Ireland, the sampling approach for the survey was firstly stratified according to 15 broad regions and five different community types. This approach was to ensure that all data generated could be analysed by the Nomenclature of Territorial Units for Statistics (NUTS) II and III regions, in addition to a range of urban and rural classifications. Within each of these broad regions, the

	Option A	Option B	No Action
Mountain land	 Some action	 A lot of action	 No action
Stonewalls	 A lot of action	 Some action	 No action
Farmyard tidiness	 A lot of action	 Some action	 No action
Cultural heritage	 Some action	 A lot of action	 No action
Expected annual cost	€ 80	€ 20	€ 0

Figure 1. Example of a choice task presented to respondents during the discrete choice experiment

appropriate number of primary sampling units, that is Electoral Divisions (EDs), was chosen. The second stage of the sampling procedure involved the systematic sampling of individuals within each of the pre-selected EDs. At each ED, the interviewer adhered to a quota control matrix based upon the known profile of Irish adults in the NUTS II regions in terms of age within sex, and socio-economic status. Within each ED, the nucleus of each cluster of interviews was an address selected on a probability basis from the then current Register of Electors. In order to limit interviewer bias the interviewers followed a random route procedure (for example first left, next right, and so on) calling at every fifth house to complete an interview, until their quotas were fulfilled.

In total the survey was administered by experienced interviewers to a representative sample of 600 respondents drawn from the Irish adult population in 2003/4. With a further 166 potential respondents refusing to complete the interview, the overall response rate was 78 percent.

3. Modelling framework

3.1. Mixed logit model

Mixed logit models provide a flexible and computationally practical econometric method for any discrete choice model derived from random utility maximisation (McFadden and Train, 2000). The mixed logit model obviates the three limitations of standard multinomial logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors (Train, 2003). Mixed logit does not exhibit the strong assumptions of independent and identically distributed (*iid*) error terms and its equivalent behavioural association with the independence of irrelevant alternatives (IIA) property.

In mixed logit the stochastic component of utility is portioned additively into two parts (Hensher and Greene, 2003). One part is perhaps correlated over alternatives and heteroskedastic over individuals and alternatives, and another that is *iid* over alternatives and individuals:

$$U_{ni} = \beta_n' x_{ni} + \left[\eta_{ni} + \varepsilon_{ni}\right], \quad (1)$$

where U_{ni} is the utility that individual n obtains from alternative i; β_n is a vector of parameters of these variables for person n representing the individual's tastes; x_{ni} is a vector of observed explanatory variables that relate to alternative i and to individual n; η_{ni} is a random term with zero mean whose distribution over individuals and alternatives depends in general on underlying parameters and observed data relating to alternative i; and ε_{ni} is a random term with zero mean that is *iid* over alternatives, does not depend on underlying parameters or data, and is normalised to set the scale of utility (Brownstone and Train, 1999). The mixed logit class of models assumes a general distribution for η_{ni}, which can take on a number of distributional forms such as normal, lognormal, uniform or triangular (McFadden and Train, 2000). Denote the density of η_{ni} by $f(\eta_{ni}|\Omega)$ where Ω are the fixed parameters of the distribution. For a given η_{ni}, the conditional probability for alternative i over alternative j, given the set of alternatives A, is logit, since the remaining error term is *iid* extreme value:

$$L_{ni}\left(\beta_n \mid \eta_{ni}\right) = \frac{\exp\left(\beta_n' x_{ni} + \eta_{ni}\right)}{\sum_{j \in A} \exp\left(\beta_n' x_{nj} + \eta_{nj}\right)}, \tag{2}$$

where L_{ni} is the logit probability. Since η_{ni} is not given, the unconditional choice probability becomes the integral of L_{ni} over all values of η_{ni} weighted by the density of η_{ni}:

$$P_{ni}\left(\beta_n \mid \Omega\right) = \int_{\eta_{ni}} L_{ni}\left(\beta_n \mid \eta_{ni}\right) f\left(\eta_{ni} \mid \Omega\right) \eta_{ni}. \tag{3}$$

Models of this form are called mixed logit since the choice probability is a mixture of logits with $f(\cdot)$ as the mixing distribution (Brownstone and Train, 1999). The probabilities do not exhibit the IIA property and different substitution patterns may be attained by appropriate specification of $f(\cdot)$. While in most applications the mixing distribution $f(\cdot)$ is specified to be continuous, it can also be specified to be discrete, with η_{ni} taking a finite set of distinct values. In this case the mixed logit model becomes the latent class model.

The mixed logit model accommodates the estimation of individual-specific preferences by deriving individual's conditional distribution based (within sample) on their known choices x^n and y^n (that is prior knowledge) (Hensher and Greene, 2003; Train, 2003; Sillano and Ortúzar, 2005). These conditional parameter estimates are strictly same-choice-specific parameters, or the mean of the parameters of the sub-population of individuals who, when faced with the same choice task, made the same choices. This is an important distinction since it is not possible to establish, for each individual, their unique set of estimates but rather identify a mean, and standard deviation, estimate for the sub-population who made the same choice (Hensher *et al.*, 2005a). Individual-specific WTP estimates can be achieved by applying Bayes' theorem to derive the expected value of the ratio between the rural landscape attribute parameter estimate (*land*) and the parameter estimate for the cost attribute (*cost*) for individual n:

$$E\left[\mathrm{WTP}^n\right] = E\left[-\frac{\beta^n_{land}}{\beta^n_{cost}}\right] = \int_{\beta^n} \beta^n P\left(\beta^n \mid y^n, x^n\right) \, d\beta^n. \tag{4}$$

It is well known that given two outcomes A and B, Bayes' theorem relates $P(B|A)$ to the conditional probability of $P(BA)$ and the two marginal probabilities $P(A)$ and $P(B)$ as follows:

$$P(B \mid A)=\frac{P(A \mid B)P(B)}{P(A)}. \tag{5}$$

So, substituting in

$$E\left[\mathrm{WTP}^n\right]=E\left[-\frac{\beta^n_{land}}{\beta^n_{cost}} \mid y^n, x^n\right]=\int_{\beta^n} -\frac{\beta^n_{land}}{\beta^n_{cost}} \frac{P\left(y^n, x^n \mid \beta^n\right)P\left(\beta^n\right)}{P\left(y^n, x^n\right)} \; d\beta^n,$$

$$=\int_{\beta^n} -\frac{\beta^n_{land}}{\beta^n_{cost}} \frac{P\left(y^n, x^n \mid \beta^n\right)P\left(\beta^n\right)}{\int_{\beta^n} P\left(y^n, x^n \mid \beta^n\right)P\left(\beta^n\right) \; d\left(\beta^n\right)} \; d\beta^n,$$

$$=\frac{\int_{\beta^n} -\frac{\beta^n_{land}}{\beta^n_{cost}} P\left(y^n, x^n \mid \beta^n\right)P\left(\beta^n\right) \; d\left(\beta^n\right)}{\int_{\beta^n} P\left(y^n, x^n \mid \beta^n\right)P\left(\beta^n\right) \; d\left(\beta^n\right)}. \tag{6}$$

With knowledge of the β estimates this can be approximated by simulation as follows:

$$\hat{E}\left[\mathrm{WTP}^n\right]=\frac{\frac{1}{R}\sum_R -\frac{\hat{\beta}^n_{land}}{\hat{\beta}^n_{cost,r}} L\left(\hat{\beta}^n_r \mid y^n, x^n\right)}{\frac{1}{R}\sum_R L\left(\hat{\beta}^n_r \mid y^n, x^n\right)}. \tag{7}$$

where L is the logit probability and R is the number of repetitions or draws. In this way the individual-specific WTP estimates are obtained conditional on all the information from the discrete choice experiment interview.

Computation of mixed logit choice probabilities using classical estimation procedures typically requires Monte Carlo integration. The basis of this computation is the generation of pseudo-random sequences that are intended to mimic independent draws from the underlying distribution of the random variable of integration. An alternative approach proposed by Bhat (2001) and Train (1999) replaces these pseudo-random sequences with sequences based on a deterministic Halton sequence. One-dimensional Halton sequences are created using any prime number $p(\geq 2)$. The unit interval [0,1] is divided into p equally-sized segments, and the endpoints or breaks of these segments form the first p numbers in the Halton sequence. Successive numbers in the sequence are generated by further subdividing each segment into p equally-sized segments and adding the breaks in a particular order. The resulting Halton draws thus achieve greater precision and coverage for a given number of draws than pseudo-random draws, since successive Halton draws are negatively correlated and therefore tend to be self-correcting (Train, 2003). Accordingly many fewer draws are needed to assure reasonably low simulation error in the estimated parameters. In fact both Bhat (2001) and Train (1999) demonstrate that for a mixed logit model, 100 Halton draws provided results that were more accurate than 1,000 pseudo-random draws. Overall the application of Halton draws allows a decrease in computation time without sacrificing precision. However while multi-dimensional Halton sequences generally provide better coverage than the corresponding pseudo-random number sequences, problems with high correlation can occur between sequences constructed from higher primes, and thus sequences used in higher dimensions. To ameliorate this, modified procedures such as scrambled and shuffled Halton draws have been used (see, for example, Bhat, 2003; Hess and Polak, 2003). Both these sequences have been found to outperform the standard Halton sequence. As a result shuffled Halton sequences, with 100 draws, are used in this paper to estimate the mixed logit model.

A key element of the mixed logit model is the assumption regarding the distribution of each of the random parameters. Random parameters can take a number of predefined functional forms, the most popular being normal, lognormal, uniform and triangular (Hensher *et al.*, 2005a). In most applications, such as Layton and Brown (2000), Revelt and Train (1998), and Train (1998), the random parameters are specified as normal or lognormal. Greene *et al.* (2005), and Greene *et al.* (2006) have used uniform and triangular distributions. However it is well known that choices of some commonly employed mixing distribution implies behaviourally inconsistent WTP values, due to the range of taste values over which the distribution spans. Normal and log-normal distributions are particularly problematic (Train and Weeks, 2005). This is due to the presence of a share of respondents with the 'wrong' sign in the former, and the presence of fat tails in the latter. This is of particular importance in a study concerned with improvements from the status-quo, on which taste intensities are expected to be positive. For a general discussion on bounding the range of variation in random utility models see Train and Sonnier (2005) who propose a Bayesian estimation approach and Train and Weeks (2005) for an application of bounding directly to the expenditure function. Following Hensher *et al.* (2005b), a bounded triangular distribution is used in this paper in which the location parameter is constrained to be equal to its scale. Such a constraint forces the distribution to be bounded over a given orthant, the sign of which is the same as the sign of the location parameter. To allow for heterogeneous preferences among respondents for all attributes within the discrete choice experiment they are all specified as random. In practice, for all random parameters associated with the various categories of rural landscape improvements it is assumed that $\beta \sim \tau(\theta)$, where θ is both the location and scale parameter of the triangular distribution $\tau(\cdot)$. This includes the cost attribute, which is bounded to the negative orthant.

3.2. Random effects model

As an extension to the empirical application of WTP for rural landscape improvements, a panel data model can be considered. The methodology used for panel data has some benefits for two important problems of cross-sectional data analysis; unobserved heterogeneity and omitted variable bias. Since a typical cross-sectional data analysis is built on the homogeneity of the given sample, unobserved heterogeneity is always a potential critique for most cross-sectional analyses. In contrast, panel data models can control for unobserved heterogeneity by parametrising it as having either a fixed effect or a random effect. Controlling for unobserved heterogeneity helps to achieve more accurate prediction. In the present study, panel data models allow a respondent's WTP for one attribute, or attribute level, to be correlated with their WTP for another attribute, or attribute level. Hence, if it is believed that an individual's WTP for one attribute, or attribute level, is useful information to predict their WTP for another attribute, or attribute level, models for panel data are at least an intuitively appealing methodology. With panel data, it is also possible to control for some types of omitted variables even without observing them. In this empirical example this can be achieved by observing changes in WTP across the different rural landscape improvements, whereby the omitted variables are assumed to differ between individuals but to be constant across the different rural landscape improvements and/or *vice versa*.

In the context of cross-sectional analysis, panel data procedures are used to account for systematic group effects. Here the subgroups within the data were created by 'stacking' the WTP estimates for each of the rural landscape improvements held by each of the individuals. Beyond this, the basic econometric specification of the model assumes a number of factors are determinants of WTP:

$$\text{WTP}_{na} = \alpha_n + \beta' x_{na} + \varepsilon_{na} \tag{8}$$

where n represents a given respondent, a is a given landscape attribute and/or level, α_n is an intercept term which varies by respondent n and β is a vector of parameters for the observed explanatory variables, x_{na}. Assuming that the same factors influence WTP for each respondent, subject to an additional error term that differs for each individual respondent, implies the random effects model, which assumes $\alpha_n = \alpha + v_n$. The α_n's represent independent random variables with the same mean (α) and variance (σ_v^2). This introduces two error terms in the equation, with v_n capturing a respondent's effect on WTP and ε_n being the typical idiosyncratic measurement error related to differences across the landscape attributes and/or levels. The individual-specific error term, v_n, is assumed to be uncorrelated with the errors of the variables. Under these circumstances v_n is heterogeneity specific to an respondent and is constant across all WTP estimates observed for this respondent. The random error ε_n is specific to a particular observation. For v_n to be properly specified, it must be orthogonal to the individual effects. Because of the separate individual error term, these models are sometimes called one-way random effects models. Owing to this intra-panel variation, the random effects model has the distinct advantage of allowing for panel-invariant variables to be included among the regressors. Estimates for the parameters and constant term in this model are obtained with generalised least squares.

For all ensuing random effects models the dependent variable is the individual-specific WTP estimate obtained for the landscape improvements. The independent regressors are a combination of dummy variables denoting the extent and/or type of the rural landscape improvement, experimental variables which assess the internal consistency of the respondent's choices and personal variables which describe the respondent. To tease out the effect of various forms of axiomatic violations of rational preferences on WTP four dummy variables are included. In particular, these examine the influence of learning and/or fatigue effects, lexicographic preferences, non-monotonic preferences and unstable preferences on the individual-specific WTP estimates. The influence of learning and/or fatigue effects on WTP are captured with the inclusion of a dummy variable indicating the questionnaire version. This dummy variable denotes whether respondents had already completed the other discrete choice experiment included in the questionnaire. The bearing of respondents employing lexicographic decision-making rules is also examined by including a dummy variable which signals whether or not respondents stated they did not consider one or more attributes when reaching their decision in the discrete choice experiment. Monotonicity of responses within the discrete choice experiment was tested by including a choice task with a dominant alternative. In this choice task Option A was at least as good as Option B in terms of every attribute. Respondents who failed to detect the dominant alternative are denoted with a dummy variable called non-monotonic preferences. Preference stability within the discrete choice experiment was assessed by asking respondents to complete the same choice task twice, once at the beginning of the experiment and again at the end of the experiment. Respondents who choose a different alternative in the repeat choice task are denoted with a dummy variable labelled unstable preferences. Personal explanatory variables are also modelled. To distinguish respondents who reside in the Border Midland and Western region in Ireland a location dummy variable is included. Unlike the rest of Ireland, this region retained the Objective 1 status for the purpose of European Union Structural Funds for the full period to 2006. Community type, which is simply a dummy variable indicating whether or not the respondent resides in a rural ED, is also modelled. To gauge the effect of the respondent's income on their WTP for rural landscape improvements their gross annual income divided by 10,000 enters the regression. The age of the respondent in years and a gender dummy variable indicating whether or not the respondent is a male are also regressed against WTP.

4. Results

The parameter estimates obtained from the mixed logit model are reported in Table 1. At convergence, the log-likelihood function is -3649.81. The model is found to be statistically significant with a χ^2 statistic of 2152.84, which is beyond the χ^2 critical value of 16.92 (with 9 degrees of freedom at alpha equal to 0.05). In addition to all of the attributes being found

Table 1

Mixed logit model results

	Mean		Scale	
Attributes	Beta	*t*-ratio	Beta	*t*-ratio
Mountain land: a lot of action	1.014	15.943	1.014	15.943
Mountain land: some action	0.611	10.357	0.611	10.357
Stonewalls: a lot of action	0.974	15.287	0.974	15.287
Stonewalls: some action	0.673	11.106	0.673	11.106
Farmyard tidiness: a lot of action	0.832	14.099	0.832	14.099
Farmyard tidiness: some action	0.527	9.063	0.527	9.063
Cultural heritage: a lot of action	0.671	11.271	0.671	11.271
Cultural heritage: some action	0.609	10.546	0.609	10.546
Cost	-0.013	-9.911	0.013	9.911
Log-likelihood	-3649.81			
χ^2	2152.84			
Pseudo-R^2	0.23			

significant, they are also estimated with the expected signs. As respondents had higher preferences for the a lot of action level *vis-à-vis* the some action level for all landscape attributes, theoretical expectations of marginal utilities of improvement are also observed. However, in the case of the cultural heritage attribute, the estimated coefficients for a lot of action and some action are found to be relatively comparable.

To convey the location and variation information regarding the distributions of the individual-specific WTP estimates obtained using equation (7) for the rural landscape improvements, box-plots are presented in Figure 2. Box-plots, sometimes referred to as box and whisker plots, are a non-parametric method and are graphical devices which can be used to capture a large amount of information. The box-plots in Figure 2 show the median, notches to indicate the 95 percent confidence interval of the median and 'hinges' corresponding with the first and third quartile of a distribution (that is, the 25th and 75th percentile points in the cumulative distribution) for each of the rural landscape improvements. Inspection of the box-plots identifies that the landscape improvements with the highest individual-specific WTP estimates are associated with the mountain land and stonewalls attributes at the a lot of action level. Median WTP values for these improvements are both found to be in the region of €85 per year. In line with *a priori* theoretical expectations the monotonicity in the intensity of

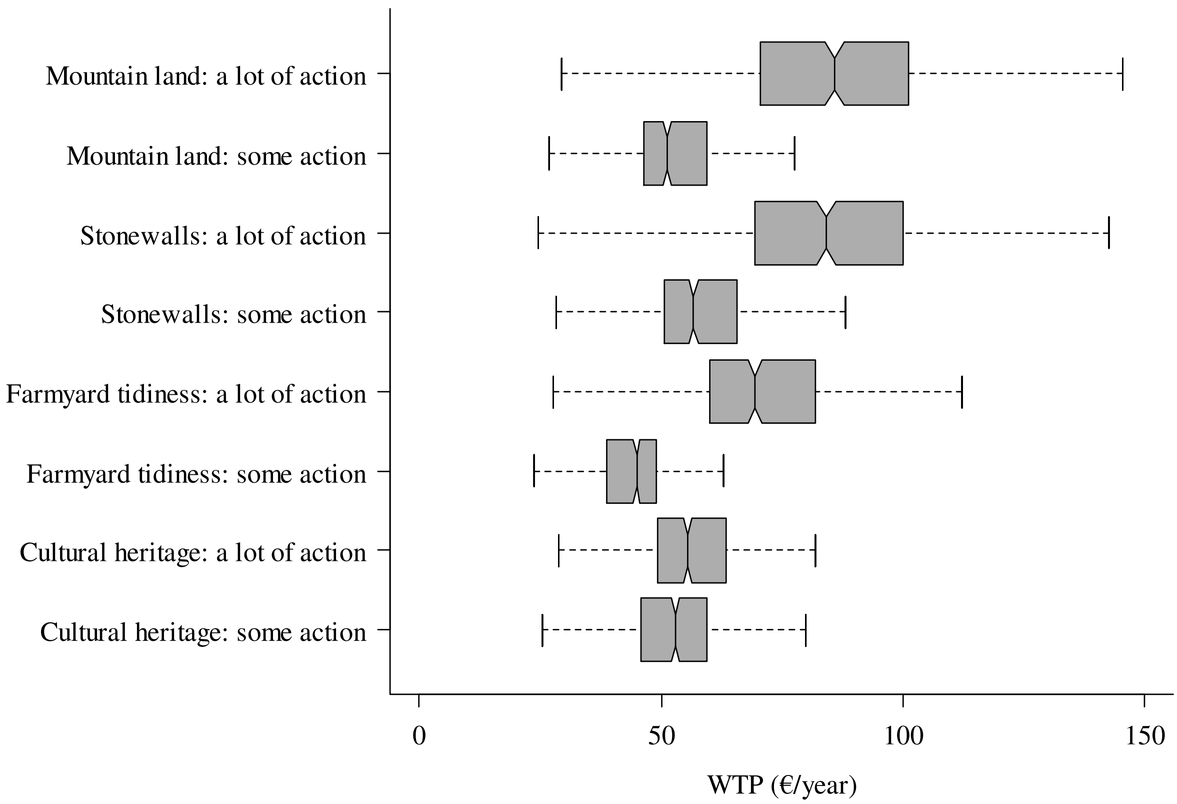

Figure 2. Box-plots of WTP for the rural landscape improvements

improvements is respected in all cases as WTP for a lot of action is always higher that for some action. This is supported by the fact that non-overlapping notches indicate the rejection of the null that the median WTP estimates for the two levels of action are equal.

Table 2 presents the estimates of the WTP model based on the specification outlined in equation (8) for each of the rural landscape attributes. For each attribute, the panels were created by pooling the WTP estimates for the two levels of rural landscape improvement, that is a lot of action and some action. A number of findings can be reported. The constant terms are found to be highly significant. The dummy variable used to denote the attributes at the a lot of action level are positive, as expected, and highly significant for all rural landscape attributes. Close inspection of the coefficient suggests that this difference is only €3.61 per year in the case of the cultural heritage attribute. For the remaining attributes this difference is found to be over €25 per year. This is supportive of the findings depicted in the box-plots in Figure 2.

Table 2

Random effects models for each of the rural landscape attributes

	Mountain Land		Stonewalls		Farmyard Tidiness		Cultural Heritage	
Parameters	Beta	*t*-ratio	Beta	*t*-ratio	Beta	*t*-ratio	Beta	*t*-ratio
Constant	49.133	18.778	54.243	19.841	41.273	21.724	49.287	27.281
A lot of action	33.227	39.731	26.678	35.029	25.988	44.999	3.607	8.749
Version	2.680	1.909	1.636	1.112	1.871	1.833	2.340	2.399
Lexicographic preferences	-7.189	-5.077	-7.602	-5.122	-5.698	-5.536	-4.799	-4.877
Non-monotonic preferences	3.187	1.833	6.216	3.411	6.197	4.903	4.808	3.980
Unstable preferences	1.592	1.023	0.621	0.380	0.023	0.021	0.834	0.771
Location	-4.927	-2.997	-3.391	-1.968	-2.347	-1.964	-3.517	-3.079
Community type	2.831	1.869	1.996	1.258	3.176	2.884	2.775	2.637
Income	0.911	2.178	0.993	2.265	0.413	1.358	0.621	2.138
Age	0.039	0.928	0.053	1.204	0.030	0.979	0.035	1.192
Gender	0.221	0.161	-0.870	-0.605	0.655	0.657	-0.304	-0.319
σ_{ε}^2	209.82		174.01		100.06		50.99	
σ_{v}^2	175.58		221.13		98.23		109.95	
Lagrange multiplier test	126.79		190.15		149.52		282.03	
R^2	0.44		0.35		0.49		0.11	

In line with findings discussed in Caussade *et al*. (2005) and Holmes and Boyle (2005), there is some evidence to suggest that learning and/or fatigue accumulated over the course of the discrete choice experiments has an impact on WTP. Interestingly, the dummy variable for versions is found to be positive for all attributes. This would suggest that higher WTP estimates are obtained from the choice tasks in the latter stage of the questionnaire. However, this learning and/or fatigue effect is found to be only significant for the cultural heritage attribute. Similar to results reported in Hensher *et al*. (2005b), respondents who employed lexicographic decision-making rules are observed to have significantly lower WTP estimates for all attributes. This may be due to the fact that respondents who do not make trade-offs between all of the attributes do not have a relative price and no tangency with the production frontier. In fact, *ceteris paribus*, respondents who stated they ignored at least one of the attributes have a WTP value for improvements associated mountain land and stonewalls that is €7 per year lower than those who stated they considered all attributes. This gives a clear message on the importance of assessing non-compensatory preferences. Previous research (see, for example, Johnson and Matthews 2001; Foster and Mourato, 2002; San Miguel *et al.* 2005) led to suggestions that identification of irrational respondents is desirable to test sensitivity of WTP estimates to violations of economic theory. This suggestion is supported by the evidence in Table 2. The non-monotonic dummy variable was positive for all attributes and with the exception of mountain land was also significant at conventional levels. Although not significant, the dummy variable indicating whether or not respondents had unstable preferences is also positive for all rural landscape attributes. This provides some evidence that respondents who hold inconsistent preferences and choose randomly tend to have higher WTP estimates than those with consistent preferences.

In line with expectations, respondents residing in Midland and Western region are found to have significantly lower WTP estimates for the rural landscape improvements. The difference is greatest for improvements relating to mountain land and least for those concerning farmyard tidiness. Community type is found to be positive for all attributes, which implies that other things being equal respondents residing in a rural ED have a higher WTP for the rural landscape improvements. However, this is only significant at conventional levels for the farmyard tidiness and cultural heritage attributes. For these attributes respondents residing in a rural ED were, on average, WTP €3.18 and €2.78 per year more respectively than those not residing in a rural ED. In line with theoretical expectations, WTP for rural landscape improvements is positively related to income. As signified by the *t*-ratios, it is found to be significant for all attributes except farmyard tidiness. Despite being significant for three attributes, respondent's income is found to have a relatively small bearing on WTP. Other things remaining constant, for every €10,000 increase in respondent's annual gross income, WTP for improvements associated with mountain land, stonewalls and cultural heritage rises by only €0.91, €0.99 and €0.62 per year respectively. WTP for all landscape attributes is also found to increase with the age of the respondents. However, this relationship is not found to be statistically significant for any of the attributes. *Prima facia*, male respondents appear to have higher WTP for mountain land and farmyard tidiness, whereas female respondents seem to attach higher values to rural landscape improvements relating to stonewalls and cultural heritage. Closer inspection of the *t*-ratios, however, fails to support either of these findings.

Also of interest are the variances of the two error terms, particularly with respect to changes between landscape attributes. The total variance varies considerably across the four models. The models for stonewalls and mountain land are found to have the greatest variance. The random effects model for cultural heritage has the greatest variance in the error term across respondents. In fact, almost 70 percent of the variance of the cultural heritage model is due to the random respondent effects. In comparison, less than half of the variance of the mountain land and stonewalls attributes are due to random respondent effects. Table 2 also lists the test results for appropriateness of using the random effects models. The Lagrange multiplier test, developed by Breusch and Pagan (1980), is used to establish whether the hypothesis σ_v^2 is equal to zero may be rejected. The statistic is asymptotically χ^2 distributed with one degree of freedom. Since all of the Lagrange multiplier test statistics exceed the χ^2 critical value of 3.84 (with one degree of freedom at alpha equal to 0.05), they all pass this test. This implies that the random effects models are more appropriate than ordinary least squares.

Reported in Table 3 is a further random effects model. This model pools WTP for all of the rural landscape attributes. The landscape attributes are distinguished by the inclusion of three dummy variables, with the cultural heritage being the base, or reference, attribute. Inspection of the coefficients indicate that improvements concerning mountain land, stonewalls and farmyards attain significantly higher WTP values than those concerning cultural heritage sites. Corresponding with theoretical expectations, higher WTP values are found for improvements associated with a lot of action than similar improvements concerning only some action. The version dummy variable was found to be positive but not significant. Similar to the models for the separate attributes reported in Table 2, respondents who ignored

Table 3

Pooled random effects model for all rural landscape attributes

Parameters	Beta	*t*-ratio
Constant	40.063	18.602
Mountain land	14.530	29.696
Stonewalls	16.310	33.334
Farmyard tidiness	2.845	5.814
A lot of action	22.375	64.671
Version	2.131	1.845
Lexicographic preferences	-6.322	-5.425
Non-monotonic preferences	5.102	3.566
Unstable preferences	0.767	0.599
Location	-3.546	-2.621
Community type	2.694	2.162
Income	0.735	2.134
Age	0.039	1.133
Gender	-0.074	-0.066
σ_{ε}^2	143.65	
σ_{v}^2	172.03	
Lagrange multiplier test	4990.87	
R^2	0.38	

at least one of the attributes are found to have a significantly lower WTP in the pooled WTP model in Table 3. On average, these respondents were WTP €6.32 per year less than respondents who considered all attributes when reaching their decisions. In contrast, respondents with non-monotonic preferences are found to have significantly higher WTP estimates. The unstable preferences dummy variable is positive but not significant. Whereas respondent residing in the Objective 1 region have significantly lower WTP estimates, respondents living in a rural ED have significantly higher WTP estimates. Income is found to have a positive and significant effect on WTP. The age and gender of the respondents do not appear to have any significant bearing on WTP. Inspection of the variances of the two error terms indicates that over half of the total variance is attributable to random respondent effects. Importantly, the model is also found to pass the Lagrange multiplier test.

5. Conclusions

Reported in this paper were the findings from a discrete choice experiments that was carried out to address the value of a number of rural landscape improvement measures under an agri-environmental scheme in the Republic of Ireland. The rural landscape improvements in question were the protection of mountain land from overstocking, enhancement of the visual aspect of stonewalls, farmyards and farm heritage buildings. Since valuation of landscapes are very subjective, and verbal descriptions can be interpreted differently on the basis of individual experience, each level of improvement was qualified and presented to respondents using photo-realistic simulations to accurately represent the landscape attributes under different management practices and levels of agricultural intensity and improvement. This study also attempted to take stock of all the main advances in the areas of multi-attribute stated preference techniques. In particular, following recent results in market research, a sequential experimental design with an informative Bayesian update to improve the efficiency of estimates was implemented.

Using a mixed logit specification this paper reported posterior estimates of welfare, in the form of the distribution of marginal WTP values, rather than focusing on more conventional estimates of central tendency based on *a priori* statistics. Distributions were found to be obviously more informative than single values, and they should thus be pursued when possible. Pooling the individual-specific WTP values for each of the rural landscape improvement measures provided a rich dataset which enabled the exploration of the inter-individual differences and intra-individual dynamics of WTP using random effects models. This methodology helped to provide more accurate descriptions of WTP as observations for one attribute, or level, were shown to be supplemented with observations for other attributes, or levels. From the policy perspective, the overall results of this study seem to indicate that the benefits from improving rural landscapes are of considerable magnitude. Highest WTP values were found for protecting mountain land and stonewalls, lowest for preserving farm heritage buildings, with maintaining tidy farmyards ranking in between. Monotonicity in the intensity of improvements was also respected as WTP for a lot of landscape improvement was always higher than for some improvement. The approach revealed evidence of a high sensitivity of implied distributions of individual-specific WTP estimates to a number of variables which assessed the internal validity and consistency of the choices made by respondents during the discrete choice experiment. This finding suggests some caution when WTP estimates obtained from the discrete choice experiment methodology are used for policy appraisal. Discrete choice experiment studies should, therefore, incorporate procedures for identifying respondents who show signs of learning and/or fatigue and lexicographic, non-monotonic or unstable preferences to help evaluate the sensitivity of the inclusion and exclusion of such respondents on WTP. The magnitude of WTP for rural landscape improvements was also found to be sensitive to personal characteristics of the respondents.

References

Bhat, C. R. 'Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model', *Transportation Research Part B*, Vol. 35, (2001) pp. 677-693.

Bhat, C. R. 'Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences', *Transportation Research Part B*, Vol. 37, (2003) pp. 837-855.

Breusch, T. S. and Pagan, A. R. 'The Lagrange multiplier test and its application to model specifications in econometrics', *Review of Economic Studies*, Vol. 47, (1980) pp. 239-253.

Brownstone, D. and Train, K. E. 'Forecasting new product penetration with flexible substitution patterns', *Journal of Econometrics*, Vol. 89, (1999) pp. 109-129.

Campbell, D. *Discrete Choice Experiments Applied to the Valuation of Rural Environmental Landscape Improvements* (Unpublished PhD thesis, Faculty of Medicine, Health and Life Sciences, Queen's University Belfast, 2006).

Caussade, S., Ortúzar, J. D., Rizzi, L. I. and Hensher, D. A. 'Assessing the influence of design dimensions on stated choice experiment estimates', *Transportation Research Part B*, Vol. 39, (2005) pp. 621-640.

Emerson, H. J. and Gillmor, D. A. 'The Rural Environment Protection Scheme of the Republic of Ireland', *Land Use Policy*, Vol.16, (1999) pp. 235-245.

Ferrini, S. and Scarpa, R. 'Designs with a-priori information for nonmarket valuation with choice-experiments: a Monte Carlo study' *Journal of Environmental Economics and Management*, forthcoming.

Foster, V. and Mourato, S. 'Testing for consistency in contingent ranking experiments', *Journal of Environmental Economics and Management*, Vol. 44, (2002) pp. 309-328.

Greene, W. H. *Econometric Analysis*, 5th edn (New York: Prentice Hall, 2003).

Greene, W. H., Hensher, D. A. and Rose, J. ' Using classical simulation-based estimators to estimate individual WTP values', In R. Scarpa and A. Alberini (eds.), *Applications of Simulation Methods in Environmental and Resource Economics* (Dordrecht: Springer, 2005, pp. 17-34).

Greene, W. H., Hensher, D. A. and Rose, J. 'Accounting for heterogeneity in the variance of unobserved effects in mixed logit models', *Transportation Research Part B*, Vol. 40, (2006) pp. 75-92.

Hanley, N. D., Mourato, S. and Wright, R. E. 'Choice modelling approaches: a superior alternative for environmental valuation?', *Journal of Economic Surveys*, Vol. 15, (2001) pp. 435-462.

Hensher, D. A. and Greene, W. H. 'The mixed logit model: the state of practice', *Transportation*, Vol. 30, (2003) pp. 133-176.

Hensher, D. A., Rose, J. and Greene, W. H. *Applied Choice Analysis: a Primer* (Cambridge: Cambridge University Press, 2005a).

Hensher, D. A., Rose, J. and Greene, W. H. 'The implications on willingness to pay of respondents ignoring specific attributes', *Transportation*, Vol. 32, (2005b) pp. 203-222.

Hess, S. and Polak, J. W. (2003) *An Alternative Method to the Scrambled Halton Sequence for Removing Correlation Between Standard Halton Sequences in High Dimensions* (Paper presented to the European Regional Science conference, Jyväskylä, 2003) [Online]. Available at: http://www.ersa.org/ersaconfs/ersa03/cdrom/papers/406.pdf [Last accessed 20 December 2006].

Holmes, T. D. and Boyle, K. J. 'Dynamic learning and context-dependence in sequential, attribute-based, stated-preference valuation questions', *Land Economics*, Vol. 81, (2005) pp. 114-126.

Hsiao, C. *Analysis of Panel Data*, 2nd edn (Cambridge: Cambridge University Press, 2003)

Johnson, F. R. and Matthews, K. E. 'Sources and effects of utility-theoretic inconsistency in stated-preference surveys', *American Journal of Agricultural Economics*, Vol. 83, (2000) pp. 1328-1333.

Kanninen, B. J. 'Optimal design for multinomial choice experiments', *Journal of Marketing Research*, Vol. 39, (2002) pp. 214-227.

Layton, D. F. and Brown, G. 'Heterogeneous preferences regarding global climate change', *The Review of Economics and Statistics*, Vol. 82, (2000) pp. 616-624.

Louviere, J. J., Hensher, D. A. and Swait, J. *Stated Choice Methods: Analysis and Application* (Cambridge: Cambridge University Press, 2003).

Lusk, J. L. and Norwood, F. B. 'Effect of experimental design on choice-based conjoint valuation estimates', *American Journal of Agricultural Economics*, Vol. 87, (2005) pp. 771-785.

McFadden, D. L. and Train, K. E. 'Mixed MNL models for discrete response', *Journal of*

Applied Econometrics, Vol. 15, (2000) pp. 447-470.

Nerlove, M. (ed.) *Essays in Panel Data Econometrics* (New York: Cambridge University Press, 2002).

Revelt, D. and Train, K. E. 'Mixed logit with repeated choices: households' choices of appliance efficiency level', *The Review of Economics and Statistics*, Vol. 80, (1998) pp. 647-657.

Sándor, Z. and Wedel, M. 'Profile construction in experimental choice designs for mixed logit models', *Marketing Science*, Vol. 21, (2002) pp. 455-475.

San Miguel, F., Ryan, M. and Amaya-Amaya, M.. ''Irrational' stated preferences: a quantitative and qualitative investigation', *Health Economics*, Vol. 14, (2005) pp. 307-322.

Scarpa, R., Campbell, D. and Hutchinson, W. G. (2005) *Individual Benefit Estimates for Rural Landscape Improvements: The Role of Sequential Bayesian Design and Response Rationality in a Choice Experiment Study* (Paper presented to the European Association of Environmental and Resource Economists conference, Bremen, 2005).[Online]. Available at: http://www.webmeets.com/files/papers/EAERE/2005/326/Scarpa%2C%20Campbell%20and%20Hutchinson%20%5BEAERE%202005%5D.pdf [Last accessed 20 December 2006].

Schläpfer, F. and Hanley, N. D. 'Do local landscape patterns affect the demand for landscape amenities protection?', *Journal of Agricultural Economics*, Vol. 54, (2003) pp. 21-34.

Sillano, M. and Ortúzar, J. D. 'Willingness-to-pay estimation with mixed logit models: some new evidence', *Environment and Planning A*, Vol. 37, (2005) pp. 525-550.

Train, K. E. 'Recreation demand models with taste differences over people', *Land Economics*, Vol. 74, (1998) pp. 230-239.

Train, K. E. Halton sequences for mixed logit (Berkeley: University of California, 1999) [Online]. Available at: http://elsa.berkeley.edu/wp/train0899.pdf [Last accessed 20 December 2006].

Train, K. E. *Discrete Choice Methods With Simulation* (Cambridge: Cambridge University Press, 2003).

Train, K. E. and Sonnier, G. 'Mixed logit with bounded distributions of correlated partworths', In R. Scarpa and A. Alberini (eds.), *Applications of Simulation Methods in Environmental and Resource Economics* (Dordrecht: Springer, 2005, pp. 117-134).

Train, K. E. and Weeks, M. 'Discrete choice models in preference space and willing-to-pay space', In R. Scarpa and A. Alberini (eds.), *Applications of Simulation Methods in Environmental and Resource Economics* (Dordrecht: Springer, 2005, pp. 1-16).

Wooldridge, J. *Econometric Analysis of Cross Section and Panel Data* (Massachusetts: MIT Press, 2002).