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The effect of using labelled alternatives in stated choice experiments: an exploration focusing on farmland walking trails in Ireland

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Abstract

Discrete choice experiment data aimed at eliciting the demand for recreational walking trails on farmland in Ireland is used to explore whether some respondents reach their choices solely on the basis of the alternative's label. To investigate this type of processing strategy, the paper exploits a discrete mixtures approach which encompasses random parameters for the attributes. We find evidence that respondents employ different processing strategies for different alternatives and differences in processing emerge between rural and urban based respondents. Results highlight that model fit and policy conclusions are sensitive to assumptions related to processing strategies among respondents.

Keywords: Discrete choice experiments, processing strategies, discrete mixtures, rural and urban comparison, outdoor recreation, welfare estimates.

1 Introduction

For many years the economic assessment of recreational goods and services has been of interest to policy-makers and the academic community. This desire to value non-market recreational goods has resulted in a large number of recreational valuation studies using both revealed and stated preference methodologies (e.g., von Haefen and Phaneuf, 2003; Train, 1998; Hynes et al., 2008; Christie et al., 2007; Hanley et al., 2002). Since the work by Adamowicz et al. (1994), the discrete choice experiment (DCE) methodology has become an established and accepted stated preference approach for valuing the recreational benefits associated with environmental goods and services. The methodology has strong theoretical underpinnings as it is both consistent with the Lancasterian microeconomic approach to utility derivation (Lancaster, 1966) and is behaviourally grounded in random utility theory (McFadden, 1974).

A fundamental decision when designing DCEs is whether to use labelled or unlabelled choice tasks. Both labelled and unlabelled choice experiments have been widely applied in the literature. According to Blamey et al. (2000) an advantage of assigning labels is that responses will better reflect the emotional context in which preferences are ultimately revealed. Indeed, there is vast amount of literature on market research indicating the importance of labels to individual choices (e.g., McClure et al., 2004; Shen and Saijo, 2009). Czajkowski and Hanley (2009) argue that an alternative label is different from other attributes because it is independent from the quantifiable characteristics of the good, and thus can invoke different emotions from respondents. Indeed, within the context of recreational site choice, using labels to represent the different types of leisure activities and environmental resources has particular advantages. For example, respondents may have a predisposition toward visiting particular types of recreation sites because it could invoke memories of past fond experiences (Blamey et al., 2000). Labelling alternatives enables these factors to be captured more accurately. On the other hand, however, labelling alternatives may result in the labels having a considerably larger impact on how respondents reach their choice outcomes than may be anticipated when designing DCEs.

DCEs are generally based on the expectation that individuals substitute between quantities or combinations of goods and across all alternatives, irrespective of their label or name. This assumption allows comparisons of welfare to be made and hence enables conclusions to be drawn based on the welfare implications of different policies. This potentially provides useful advice to policy-makers because it can help inform the more efficient allocation of scarce resources. The central aim of this paper is to investigate the consistency of this substitution principle in the context of determining recreational site choice using the DCE methodology. The paper builds on increasing recognition in the DCE literature that, in addition to heterogeneity in respondents' preferences, there is heterogeneity in how respondents process information within DCEs, particularly where respondents' ignore or exclude attributes when reaching their choice outcomes (e.g., see Campbell et al., 2008; Scarpa et al., 2009; Hensher et al., 2010; Scarpa et al., 2010).

This paper seeks to explore whether or not the alternative's label has a bearing on the processing strategy adopted by respondents. In so doing, this paper develops an analytical approach to accommodate these processing strategies as well as highlighting the potential repercussions of failing to account for them. Our analysis considers data collected to determine the recreational benefits associated with developing farmland walking trails in the Republic of Ireland. Farmland recreation is specifically explored because in Ireland farmland is prevalent outside urban areas and has considerable potential to provide recreational opportunities for Irish residents (Buckley et al., 2009). In addition, among Irish residents, walking is by far the most common recreational activity (Curtis and Williams, 2005).

This paper adds to the literature in a number of ways. First, this study determines whether respondents consider all the information contained within alternatives or whether they choose solely on the basis of the label of the alternative, in this case based on the type of farmland walk. Although there is a substantial body of literature that has explored the phenomenon of attribute non-attendance, few studies have examined the effects of *non-attendance in the presence of labelled alternatives*—in spite of the fact that labelled alternatives are commonly used in stated preference studies. Both Blamey et al. (2000) and De Bekker-Grob et al. (2010) suggest that respondents have a higher propensity to ignore attributes when labelled alternatives are included in the choice experiment. This present study provides an in-depth analysis to probabilistically determine for each alternative, the proportion of respondents who made their choices based on its label only.

Second, we develop a discrete mixtures modelling approach to simultaneously accommodate heterogeneity in processing strategies and taste heterogeneity for attributes of farmland walking trails. A number of methods have been developed in the literature to date to accommodate attribute non-attendance in the estimation of discrete choice models. The most common method uses information from follow-up questions asked after the valuation experiment to assign zero parameters to the attribute(s) respondents' said they ignored (e.g., Rose et al., 2005; Carlsson et al., 2010). While this can lead to improvements in model fit, a major drawback of this approach is that information from such follow-up questions is not always available. Partly as a result of this drawback, modelling approaches that can endogenously determine whether attributes have been attended to, have been developed. Examples of modelling approaches include finite mixture models such as latent class models to probabilistically assign respondents into classes which ignore attributes (e.g., Campbell et al., 2008; Scarpa et al., 2009) and non-linear processing models that include an additional unknown parameter, randomly distributed which allows respondents to have different attribute attendance (e.g., Hensher and Rose, 2009). Other approaches include that by Hess and Hensher (2010) who infer attribute non-attendance through the analysis of the respondent-specific coefficient distribution obtained by conditioning on observed choices. In this paper, we develop an alternative modelling approach to simultaneously accommodate both heterogeneity in processing strategies and tastes for farmland walking trail attributes. This enables us to probabilistically determine the proportion of respondents who make their choice based on the label only, as well as to decipher the extent of taste differences for the attributes of farmland walking trails. Another major benefit of this modelling approach is to determine the extent to which heterogeneity in processing strategies is confounded with heterogeneity in taste, which has not been explored in detail in the literature thus far.

In the literature, research has been undertaken to determine factors that may explain the incidence of adopting processing strategies. The most obvious is because respondents may not care about the attributes they ignore. Other factors that have been considered include choice task complexity, socio-economic determinants as well as external factors related to a respondent's environment (e.g., Caussade et al., 2005; Scarpa et al., 2010; Rosenberger et al., 2003). A third contribution of this paper is to explore differences in processing strategies across a rural-urban gradient. The reasons for focusing on rural-urban differences is as follows; in the context of making recreational choices related to specific recreational terrain such as farmland, differences in processing (and preferences) between rural and urban respondents may manifest themselves because of differences in access, familiarity or perceptions of farmland walking trails. Indeed findings from the qualitative part of this study appeared to confirm these observations. In addition, evidence within the literature suggests that rural and urban respondents may differ in their preferences for outdoor recreation (e.g., Airlinghus et al., 2008; Shores and West, 2010). In this study, we determine whether differences may also exist in the processing strategies along the rural-urban gradient.

Finally, this study explores preferences for farmland recreation in Ireland using a representative sample of the Irish population. We are interested in assessing the impact on welfare estimates of accounting for both processing and taste heterogeneity in model estimation on welfare estimation as well as its implications for policy. In addition, we extend our analysis and explore the differences between rural and urban residents in Ireland on the marginal part-worths (i.e., willingness to pay (WTP)) estimates for the farmland walking attributes and on estimates of overall consumer surplus related to the different walk alternatives. This adds to the literature comparing rural-urban preferences for outdoor recreation.

Our results provide strong evidence that for each type of recreational walk a subset of respondents do not attend to any of its attributes, but rather focus solely the label used to describe it. We also find this phenomenon is more prevalent among respondents residing in urban areas compared to those residing in rural areas. There are also differences in the extent of processing strategies between different types of recreational walks. Additionally, in our empirical case-study we show that accommodating processing heterogeneity leads to significant gains in model fit and a large reduction in taste heterogeneity for the attributes—suggesting the strong likelihood of confounding between processing strategies for the alternatives and taste heterogeneity for the attributes of farmland walking trails. We also find that welfare estimates are highly sensitive to assumptions regarding heterogeneity in processing and tastes for farmland walking trail attributes. In addition, rural and urban respondents exhibit differences in preferences for the features of farmland walking trails, which is shown by their respective welfare estimates.

To examine these issues the paper is outlined as follows. The methodological approach for accommodating processing strategies related to the alternative labels is described in Section 2. Section 3 describes the background to the study and the empirical data. Section 4 presents the results from the econometric investigation and welfare estimations investigating the impact of failing to accommodate these processing strategies. Finally, Section 5 presents the discussion and conclusions.

2 Methodology

Using the conventional specification of utility where each of the alternatives are specified as j, respondents are indexed by n, choice occasions by t and the vector of attributes is represented by x, we have:

$$\begin{aligned} U_{nj_1t} &= \beta x_{nj_1t} + C_{j_1} + \varepsilon_{nj_1t} \\ &\vdots \\ U_{nj_Jt} &= \beta x_{nj_Jt} + C_{j_J} + \varepsilon_{nj_Jt}, \end{aligned} \tag{1}$$

where βs are parameters to be estimated, Cs are alternative specific constants where one or more are constrained to be zero to facilitate estimation and ε is an *iid* Gumbel distributed error term, with constant variance $\pi^2/6$, giving rise to the MNL model:

$$\Pr(j_{nt}) = \frac{\exp\left(\beta x_{njt} + C_j\right)}{\sum_{j=1}^{J} \exp\left(\beta x_{nJt} + C_J\right)}, \tag{2}$$

In this specification it is assumed that preferences are homogeneous across all observations and individuals. While in many cases this assumption may hold, a growing number of empirical studies have shown that there is often heterogeneity in the preferences that individuals hold for different attributes.

The limitations of the MNL model in accommodating preference heterogeneity have given rise to an array of models that fit under the mixed logit umbrella. Such models have a number of attractions and as discussed in McFadden and Train (2000), can provide a flexible and theoretically computationally practical econometric method for any discrete choice model derived from random utility maximisation. The central feature of mixed logit models is their ability to accommodate random taste variation (Train, 2009), which is generally shown to significantly improve model fit (Hensher and Greene, 2003; Rigby et al., 2009) as well as provide greater insights into choice behaviour (McFadden and Train, 2000) and welfare estimation (Sillano and Ortúzar, 2005; Scarpa et al., 2008; Hynes et al., 2008).

Under mixed logit models, the unconditional probability of the choices made by individual n is obtained by integrating the product of logit probabilities over the distribution of β, with $\beta \sim f(\beta|\,\Omega)$, where Ω is a vector of parameters:

$$\Pr(y_n|\Omega, x_n) = \int_{\beta} \prod_{t=1}^{T_n} \frac{\exp\left(\beta x_{njt} + C_j\right)}{\sum\limits_{j=1}^{J} \exp\left(\beta x_{nJt} + C_J\right)} f(\beta|\,\Omega) d\beta. \tag{3}$$

where y_n gives the sequence of choices over the T_n choice occasions for respondent n, i.e., $y_n = \langle i_{n1}, i_{n2}, \ldots, i_{nT_n} \rangle$. Such model specifications are commonly referred to as random parameters logit (RPL) models. These models mainly provide the analyst with information on the mean, potentially the mode, and the spread, while more flexible distributions also give additional shape information. Retrieving such information provides a rich insight into the range of taste intensities held by the respondents. Not surprisingly, RPL models have become an established and frequently used specification. Indeed, in the environmental economics literature it is now increasingly common and often expected practice to use RPL models to handle preference heterogeneity in studies aimed at eliciting recreational demand (e.g., Train, 1998; Provencher and Bishop, 2004; Murdock, 2006; Hynes et al., 2008).

Despite the advantages of the RPL model in accommodating preference heterogeneity, it is possible that some of the retrieved heterogeneity may actually be heterogeneity in the processing strategies and not random taste variation. Of central interest in this paper is the extent to which respondents process only the label of the alternative when reaching their choices. To help establish the share of respondents who focus purely on the name of the alternative and disregard the actual attributes that define the alternative, this paper purports the use of discrete mixtures (DM) approach. The advantage of DM specifications is that it can be used to provide probabilistic estimates of processing strategies relating to the alternative, whilst simultaneously conditioning the values of parameters entering the likelihood function. The approach therefore ensures that unnecessary weight is not allocated to attributes within the alternatives that were ignored by respondents.

In a DM context, the number of possible values for a parameter is finite. To facilitate the occurrence of respondents focusing only on the alternative name and ignoring the attributes that define the alternative, each of the representative utilities are specified as a function of a vector of discrete variables (δ), as follows:

$$V_{njt} = \delta_j \beta x_{njt} + \left(1 - \delta_j\right) C_j. \tag{4}$$

We specify each of the discrete variables as a dummy variable, as follows:

$$\delta_j = \begin{cases} 0 & \text{if the respondent only considered the name of alternative } j; \\ 1 & \text{if the respondent considered the attributes of alternative } j. \end{cases} \tag{5}$$

The mass points are associated with the probabilities $\pi_{\delta_j^0}$ and $\pi_{\delta_j^1}$ respectively and are subject to the following conditions:

$$0 \leq \pi_{\delta_j^0} \leq 1 \qquad 0 \leq \pi_{\delta_j^1} \leq 1 \qquad \pi_{\delta_j^0} + \pi_{\delta_j^1} = 1. \tag{6}$$

Therefore conditional on δ, the probability of respondent n's sequence of choices is given by:

$$\Pr\left(y_n | \delta, x_n\right) = \sum_{s=1}^{S} \omega_s \prod_{t=1}^{T_n} \frac{\exp\left(\delta_j \beta x_{njt} + \left(1 - \delta_j\right) C_j\right)}{\sum\limits_{j=1}^{J} \exp\left(\delta_J \beta x_{nJt} + \left(1 - \delta_J\right) C_J\right)}, \tag{7}$$

where $s = 1, ..., S$ is an index over all possible combinations of values for the J dummy variables given their two values each (i.e., $S = 2^J$). As an example with two alternatives, say A and B, $S = 4$, and with $s = 1$ relating to the case where the dummy variables are zero for both alternatives (i.e., cases where only the names of alternative A and B were considered), would provide $\omega_1 = \pi_{\delta_{nA}^0} \pi_{\delta_{nB}^0}$ and $\delta_1 = \left(\delta_{nA}^0, \delta_{nB}^0\right)$. In the empirical case-study reported in this paper, there are four labelled alternatives resulting in $S = 16$ combinations of alternative processing strategies.

With this specification of δ_j, the probabilities $\pi_{\delta_j^0}$ and $\pi_{\delta_j^1}$ have an intuitive meaning: $\pi_{\delta_j^0}$ represents the probability that all attributes associated with alternative j were neglected by the respondent and that only the name of the alternative was considered, whereas $\pi_{\delta_j^1}$ represents the probability that the attributes of alternative j were considered by the respondent. This approach has the further advantage that it is not necessary to rely on answers from follow-up and debriefing questions. Instead, this approach endogenously determines the processing strategies adopted by respondents. We also note that our DM specifications ensure that the value of $\pi_{\delta_j^1}$ reflects only the attribute influence on choice without the influence of the labelled alternatives, whereas only an alternative specific constant is estimated for those respondents who solely considered the alternative name and disregarded the attributes that made up the alternative.

Notwithstanding the ability of the DM specification to uncover the heterogeneity in processing strategies, it is unlikely that it will fully explain the preference heterogeneity associated with the attributes. For this reason, we extend our DM approach to accommodate preference heterogeneity among those respondents who did consider the attributes within the alternatives. We achieve this by combining features of equations (3) and (7), as follows:

$$\Pr\left(y_n|\delta,\Omega,x_n\right) = \sum_{s=1}^{S}\omega_s \int_{\beta} \prod_{t=1}^{T_n} \frac{\exp\left(\delta_j \beta x_{njt} + \left(1-\delta_j\right) C_j\right)}{\sum_{j=1}^{J} \exp\left(\delta_J \beta x_{nJt} + \left(1-\delta_J\right) C_J\right)} f\left(\beta|\Omega\right) d\beta. \quad (8)$$

Using such a hybrid specification we hope to address both types of heterogeneity simultaneously. To assess the merits of the different model specifications in relation to preference and processing heterogeneity, we compare and contrast the results from the four models described above. The first is the MNL model (equation (2)), with marginal utility parameters retrieved for all attributes. The second model is the standard RPL model (equation (3)), with univariate Normal distributions obtained for the attributes used to describe the alternatives (i.e., $\beta \sim \mathcal{N}\left(\mu,\sigma^2\right)$, where μ and σ are the mean and standard deviation respectively). The third model is the DM model (equation (7)), which is aimed at uncovering the extent to which respondents only processed the alternative name and gave no attention to the attributes that defined the alternative. The final model, which we label RPL-DM (equation (8)), combines elements of the RPL and DM models and simultaneously retrieves random parameters for univariate Normal distributions for the attributes of the alternative (i.e., $\beta \sim \mathcal{N}\left(\mu,\sigma^2\right)$) as well as probabilistic estimates of the proportion of respondents who attended only to the alternative name.

The RPL, DM and RPL-DM models are estimated with consideration to the repeated choice nature of the data, with variation in tastes across respondents, but not across choices for the same respondent. Since the choice probabilities in equations (3) and (8) cannot be calculated exactly (because the integrals do not have a closed form solution), we estimate these models by simulating the log-likelihood using 250 Halton draws.

While the RPL, DM and RPL-DM models facilitate random taste and/or processing strategy in the sample population, they do not directly provide any information on the likely position of a given respondent on these distributions.

For this reason we move from the unconditional (i.e., sample population level) distribution to a conditional distribution as it helps to infer the most likely location of each sampled respondent on the distributions of tastes and/or processing strategies. Following Hess (2010); Train (2009), the probability of observing a specific value along these distributions conditional on the sequence of choices of respondent n (denoted by $L(\theta|y_n)$) is given by:

$$L(\theta|y_n) = \frac{L(y_n|\theta) f(\theta)}{\int_{\theta} L(y_n|\theta) f(\theta) \, d\theta}, \tag{9}$$

where $L(y_n|\theta)$ gives the probability of observing the sequence of choices with the specific value of θ, which is a vector comprising of δ and β. Hence, $f(\theta)$ is equal to $\omega f(\beta|\Omega)$, incorporating the density associated with the discrete (i.e., δ) and continuous (i.e., β) distributions (i.e., ω and $f(\beta|\Omega)$ respectively). The integral in the denominator does not have a closed form solution. Nevertheless, the value of θ can be approximated by simulating draws of the estimated (unconditional) distributions of the variables in the model and calculating for each respondent, the probabilities (conditional on their sequence of choices to the choice tasks they were offered) associated with each random draw. Finally, deriving the average (weighted by the conditional probabilities) of the random draws returns an estimate of the conditional mean of the individual-specific distribution. Our calculations are based on the simulation of 10,000 draws.[1]

As discussed in Hess (2010) retrieving the conditional distributions provides useful information for a variety of reasons. In our context, we exploit the means obtained from these distributions to explore the possible differences between rural and urban respondents. Our motivations for this stem from evidence in previous studies (e.g., Airlinghus et al., 2008; Shores and West, 2010), which suggest differences in perceptions and preferences relating to outdoor recreation among rural and urban respondents. We hypothesize that variations in tastes and processing strategies between rural and urban respondents could arise as a result of differences in access, familiarity and perceptions of farmland walking trails, which appeared to be confirmed by the qualitative discussions undertaken prior to the DCE study. In this study we therefore undertake a comparison of the conditional means retrieved from the two subgroups to establish if differences exist in their distribution of tastes and processing strategies.

A central aspect of this study is to examine the impact of the processing strategies investigated in this paper on marginal WTP estimates for the trail attributes derived under the four models, computed using the ratio of $\beta_k / -\beta_\$$, where β_k and

[1] We fully acknowledge that the conditional estimates for each respondent have a distribution, and that our calculations provide only the expected value of the distribution. Nevertheless, this approach does give us with some information about the most likely position on the distribution.

$\beta_\$$ are the parameters for the non-cost and cost attributes respectively. In addition, we are also interested in determining the implications for estimates of consumer surplus associated with the walk alternatives. Our calculations are based on the compensating variation (CV) log-sum formula, described by Hanemann (1984), for determining the expected welfare loss (or gain) associated with the policy scenarios:

$$\mathrm{CV} = \frac{1}{-\beta_\$}\left[\ln\left(\sum_{j=1}^{J}\exp\left(V_j^1\right)\right) - \ln\left(\sum_{j=1}^{J}\exp\left(V_j^0\right)\right)\right], \tag{10}$$

where V_j^1 and V_j^0 represent the deterministic part of the indirect utility function before (i.e., situation where no walk is available) and after the policy change (i.e., situation where one of the walk alternatives is provided). Again, for the RPL, DM and RPL-DM models it is required to account for the heterogeneity. In this case the expected measure of CV needs integration over the distributions of taste and/or processing strategies (again denoted by θ) in the population:

$$\mathrm{CV} = \int_\theta \frac{1}{-\beta_\$}\left[\ln\left(\sum_{j=1}^{J}\exp\left(V_j^1\right)\right) - \ln\left(\sum_{j=1}^{J}\exp\left(V_j^0\right)\right)\right] f(\theta)\, d\theta. \tag{11}$$

This integral is also approximated by simulation from 10,000 draws of the estimated distributions for the taste and/or processing strategies.

3 Background to the study and data description

3.1 Background to the study

Across Europe and other developed countries public access for walking in the countryside is frequently enshrined in legislation and/or custom. Where neither legislation nor custom prevail, provision is often achieved through specifically designated areas such as parks. Neither legislation nor custom applies in the case of Ireland, resulting in few designated public rights. Moreover, parks developed specifically for providing recreational enjoyment are considerably limited. In addition, the vast majority of land in the Irish countryside is privately owned as farmland and a right to roam or an everyman's right of access, which is applicable in other European countries, does not prevail in Ireland. As a result, Ireland does not have a network of well defined countryside walking opportunities and many of the recreational walking opportunities in the Irish countryside are limited to public roads (for a discussion on public access issues in Ireland, see Buckley et al., 2008). However, recent research conducted by Buckley et al. (2009) suggested a willingness amongst farmers in Ireland to substantially increase the supply of recreational opportunities for walking on their land. As a result the present study sought to establish whether demand side potential exists for the creation of farmland walking trails amongst Irish residents.

The paucity of current farmland recreational opportunities in Ireland meant that stated preference methods are more suitable for valuing these recreational amenities. In addition, the multi-attribute nature of recreational walking trails make the DCE method particularly suitable to establish the value that people attach to this recreational resource and thus was the methodology chosen for this study.

3.2 Survey design and data description

The design of the DCE survey instrument involved several rounds of development and pre-testing. This process began with the gathering of opinions from a wide-range of stakeholders interested in addressing public access concerns within Ireland. The stakeholders included representatives from recreational and health bodies, tourist bodies, farming representatives and representatives from state and semi-state bodies. To further define the attributes and alternatives, a series of focus group and one-to-one discussions with members of the general public were held. Following the discussions, the questionnaire was piloted, with the aim of checking the wording of the questionnaire and the respondent's acceptance of the choice scenarios. In the final version of the questionnaire, five attributes were decided upon to describe the walking trails. These attributes were chosen on the basis of their choice relevancy to members of the general public as well as their suitability and relevance for farmland recreation. The first attribute, 'Duration', indicated the length of time needed to complete the walk. This attribute was presented at three levels with the shortest length between 1–2 hours, the medium length between 2–3 hours and the longest length between 3–4 hours. These levels were informed by discussions at focus groups as well as information on the current recreation walking activity of the Irish population. The second attribute, 'Car Park', was a dummy variable denoting the presence of car parking facilities at the walking trail. The third attribute, 'Fence', was a dummy variable used to indicate if the trail was fenced-off from livestock. The fourth attribute, 'Path and Signage', was a dummy variable to distinguish if the trail was paved and signposted. These three attributes represented the infrastructural features that were deemed important and realistic for farmland walking trails based on findings from the qualitative part of the study. The final attribute, 'Distance', denoted the distance (in kilometres) that the walk is located from the respondent's home. This attribute was later converted to a 'Travel Cost' per trip using estimates of the cost of travelling by car from the Irish Automobile Association. Findings from focus group discussions indicated that this represented a realistic and acceptable payment mechanism and corresponds to the approach taken by (e.g., Adamowicz et al., 1994; Hanley et al., 2002; Christie et al., 2007).

The focus group discussions as well as feedback from the stakeholder meetings identified four main types of farmland walks in Ireland, namely 'Hill', 'Field', 'Bog' and 'River' walks. A labelled choice experiment, with the labels representing these four main types of walk was therefore used. The attributes and levels applied to all alternatives, except in the case of the Fence attribute which, following safety concerns raised in the focus group discussions, only applied to the Field and River alternatives.

In generating the choice scenarios this study adopted a Bayesian efficient design, based on the minimisation of the D_b-error criterion (for a general overview of efficient experimental design literature, see e.g., Scarpa and Rose, 2008, and reference cited therein). Our design comprised of a panel of twelve choice tasks. For each task, respondents were asked to choose between the experimentally designed alternatives and a stay at home option. When making their choices, respondents were asked to consider only the information presented in the choice task and to treat each task separately. Respondents were further reminded that distant trails would be more costly in terms of their time and money.

The survey was administered to a sample of Irish residents in 2009 using face-to face interviews. A quota controlled sampling procedure was followed to ensure that the survey was nationally representative for the population aged 18 years and above. The quotas used were based on known population distribution figures for age, gender and region of residence taken from the Irish National Census of Population, 2006. The survey had a 61 percent response rate and the data used for model estimation includes 5,640 observations from 470 individuals.

4 Results

4.1 Estimation results

Table 1 reports the results from the four discrete choice models. As shown, the MNL model retrieves positive and significant coefficients for all farmland trail attributes—implying that, *ceteris paribus*, respondents prefer walks that are up to 2 hours duration[2], that have car parking facilities, have a fence as well as path and signage. The travel cost coefficient is estimated as significant and has the theoretically correct sign. The alternative specific constants for hill, field and river walking trails are positive and significant—implying, other things being constant, relative to staying at home respondents have a preference for these types of walks—whereas, the alternative specific constant associated with bog walks is negative, although marginally not significant at the 5 percent threshold.

Table 1 about here.

[2]Walks of up to 2 hours is included as a dummy variable, since estimated coefficients for longer walks (2–3 hours and 3–4 hours) were not statistically different from each other.

For the RPL model we specify all the non-cost attributes as having Normal distributions since it is possible that for each of these attributes, respondents may have a negative or positive preference for them. For example, for the fence attribute some respondents may like a fence for fear of livestock, while other respondents may find that a fence around a walking trail too restrictive. Similarly, whilst we would expect the majority of respondents to like car-parking facilities, there may be a proportion of respondents who prefer more natural walking trails without these types of facilities. We also follow the relatively common practice in the literature and hold the cost coefficient fixed.[3] The RPL model is associated with a vastly superior model fit compared to the MNL model. This supports our decision to accommodate taste heterogeneity for the farmland trail attributes. The RPL model recovers a high degree of taste heterogeneity for the random parameters with statistically significant standard deviations. The standard deviations are of a relatively large magnitude compared to the estimated mean. This result implies a high degree of dispersion as well as a substantial share of the distributions in both the negative and positive domains. In particular, the estimated mean for the fence attribute is not significant whereas the standard deviation is highly significant, suggesting that there is an almost equal share of respondents who dislike and like this attribute. The sign and significance of the remaining coefficients remains consistent with the MNL model except for the alternative specific constant associated with bog walks, which is now positive, albeit not significant.

Moving to the DM model, which explicitly retrieves probabilities that the attributes within specific alternatives were ignored by respondents and choices were made solely on the basis of the alternative name. We note that the model fit statistics are superior to those achieved under the MNL and RPL models. This highlights the benefit of accounting for this type of processing strategy. Looking firstly at the predicted probabilities that respondents considered only the name of the alternative reveals that they are significantly different from zero—suggesting the presence of respondents who ignored the attributes of the walk alternatives. We find that almost 40 percent of respondents are estimated to ignore the attributes of river walks, compared to approximately 12 percent for the attributes of a bog walk and approximately 25 percent for the attributes of hill and field walks respectively. The estimated alternative specific constants for respondent who focused solely on the name of the alternative are significant. The fact that these coefficients are positive and are of a relatively large magnitude suggests that respondents only ignored the attributes of the walks that they were favourably disposed to. This is also reflected by the fact that the implied rank of the alternative

[3]The use of a fixed coefficient for cost is admittedly a strong assumption, as it leads to a constant marginal utility of income across individuals as well as a fixed scale parameter. A possible solution to this could be to reparameterise the model in willingness to pay space (e.g., see Scarpa et al., 2008; Thiene and Scarpa, 2009; Train and Weeks, 2005, for further details). However, this is beyond the focus of the present paper.

specific constants are in line with the ordering of the predicted probabilities of attribute non-attendance of certain walk alternatives. With regard to the attribute coefficients, which are fixed in this model, obtained from those respondents who only looked at the attributes of the alternative irrespective of the type of walk, we find that they are significant and their sign complies with *a priori* expectations.

The final model in Table 1 is our RPL-DM specification, which builds on the RPL model, to accommodate random taste variation for the walk attributes, as well as the DM model, to address non-attendance of attributes in the presence of labelled alternatives. This specification is associated with a huge improvement in model fit from the RPL and DM models (an improvement of 616 and 488 log-likelihood units respectively at the expense of four addition parameters in both cases). Notice also that, the $\bar{\rho}^2$, AIC and BIC statistics[4] showed this improvement even after penalising for the loss of parsimony due to the increase in the number of parameters estimated. We observe that the predicted probabilities of non-attendance are similar to those attained under the DM model and similar inference can be made from the alternative specific constants obtained from those respondents who focused solely on the alternative name. The mean coefficients for the attributes are all significant as are the standard deviations, reflecting preference heterogeneity among respondents who considered the attributes of the different walking trails. A notable aspect of the RPL-DM model is the decline in the implied coefficient of variation for all the attributes compared to those suggested under the RPL model. This result suggests that there may be some confounding between taste and processing heterogeneity, whereby respondents who have clearly ignored the attributes of particular alternatives add to the extent of preference heterogeneity uncovered from the RPL model, manifested through the relatively large standard deviations compared to the mean values under the RPL model.

4.2 Rural-urban comparison of processing strategies

As previously noted, a central interest in this paper is to determine whether respondents residing in rural and urban locations exhibit differences in processing strategies related to alternative farmland walking trails. To explore this issue it is of interest to predict for each respondent whether or not they focused solely on the alternative name when reaching their decisions. For this reason we calculate the individual-specific (i.e, conditional) probabilities that the attributes within

[4]The $\bar{\rho}^2$ is an adjustment of the ρ^2 statistic, penalising for the number of parameters K. It is defined by: $\bar{\rho}^2 = 1 - \left(\left(\mathcal{L}\left(\hat{\beta}\right) - K\right) / \mathcal{L}(0)\right)$, where $\mathcal{L}\left(\hat{\beta}\right)$ and $\mathcal{L}(0)$ are the log-likelihoods for the estimated model and the model in which all parameters are set to zero respectively. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) can be used to discriminate between un-nested models by also placing a penalty on the number of parameters. The AIC is derived by: $\text{AIC} = -2\mathcal{L}\left(\hat{\beta}\right) + 2K$. The BIC is defined as follows: $\text{BIC} = -2\mathcal{L}\left(\hat{\beta}\right) + K\ln(N)$, where N is the number of observations.

each of the four walk alternatives were not attended to, which we separate along a rural-urban gradient[5]. The distributions of the retrieved conditional mean probabilities from the RPL-DM are summarised in Fig. 1.

An examination of the back-to-back histograms in Fig. 1 clearly reveals the heterogeneity in the processing strategies adopted by respondents. There is also an apparent difference between the incidence of processing strategies for different alternatives. In line with previous inferences this is most obvious for River walks (Fig. 1(d)), where the largest predicted share of respondents are estimated to ignore the attributes of this alternative. Furthermore, the incidence of focusing on only the River label is distinctly higher among urban respondents. A similar pattern is evident for Field walks (Fig. 1(c)). We also observe a slightly higher proportion of urban respondents are predicted to ignore the attributes of Hill walks (Fig. 1(a)). The attributes of the Bog walk (Fig. 1(b)) are least ignored and rural and urban respondents exhibit the most similar pattern in processing strategies for this walk alternative. The large difference between rural and urban respondents for the field and river walk alternatives may reflect the fact that watercourses and fields typify the Irish countryside and are likely to invoke different emotions among rural respondents who are more familiar with them and encounter them on a regular basis. Therefore, rural respondents may be less likely to ignore the attributes of these alternatives as they may only be willing to visit a river or field walk if the attribute levels offer something different from what they are familiar with.

Figure 1 about here.

4.3 Impact of non-attendance on welfare estimates

We report the results from our marginal WTP per trip calculations for the four model specifications in Table 2. However, in the case of the RPL, DM and RPL-DM models it is necessary to accommodate the heterogeneity in processing strategies and/or preferences. For this reason, the estimates in Table 2 for the RPL, DM and RPL-DM models are based on the parameters explaining the conditional distributions for which we also report the standard deviations. In Table 2 we report the estimates for the entire sample along with the rural and urban subsamples.

Table 2 about here.

[5]For the purpose of this case-study we define rural respondents as those who reside outside the main cities in Ireland and urban respondents as those who live in one of these cities. This classification reflects the ease with which respondents located outside the main cities can access farmland compared to their urban counterparts. The sample breakdown is 281 and 189 rural and urban respondents respectively.

We note that the implied rank orderings appear to be stable across the four models. The marginal WTP estimates obtained from the MNL model reveal that, other things being equal, the sample of respondents valued a walk that would take 1–2 hours almost €22 more than a walk that would take more than 2 hours. Results from the MNL model further suggest that all respondents value a paved and signed walking trail €12 more than a trail without paths or signage. Car parking facilities and fencing from livestock were also features that the sample of respondents were willing to pay for, approximately €7.50 and €5 respectively. Turning to the sample mean marginal WTP estimates produced from the RPL model reveals that they are of a similar magnitude to those attained under the MNL model, with the exception of the value assigned to trails with paths and signage (which increases to almost €18). We also note that the distributions of marginal WTP predicted under the RPL model appear to be relatively dispersed, indicating heterogeneous marginal WTP estimates across the sample of respondents. From the DM model, we find that the marginal WTP per trip estimates are approximately €9, €5.50, €4.50 and €8 for walks that are 1–2 hours, have car parking facilities, are fenced-off from livestock and are paved and signed respectively. While these are lower than those uncovered from the MNL and RPL models, they are more in line with those obtained from the RPL-DM model, which are generally only slightly higher. Importantly, this highlights the sensitivity in the marginal WTP estimates of accounting for the heterogeneity in processing strategies that respondents adopt when making their decisions, which is comparable to findings reported in other studies (See for example Scarpa et al., 2009). The marginal WTP distributions retrieved from the DM model exhibit some variation which is a direct result of the heterogeneity in processing strategies. However, the fact that standard deviations reported for the RPL-DM model are of considerably lower magnitude than those attained under the RPL specification suggests that the degree of preference heterogeneity uncovered by the RPL model could be exaggerated when processing strategies are not explicitly accommodated in model estimations. The findings suggest that if the researcher wishes to uncover the variation associated with marginal WTP attention should be paid to accommodating both types of heterogeneity, otherwise the distributions of marginal WTP may be biased.

For the RPL model where preference heterogeneity is facilitated, we find that urban respondents are on average willing to pay more than their rural counterparts for walks that are of a longer duration, have car parking facilities, are fenced-off from livestock and are paved and signed. For the DM model we note that the estimates between rural and urban respondents are not statistically different and reflect the fact that urban respondents had a higher propensity to ignore the attributes of the alternatives. As a result the WTP estimates for urban respondents, under this model, are slightly lower than their rural counterparts. For the RPL-DM model, where both taste and processing differences are accommodated, urban respondents exhibit higher WTP estimates for the trail attributes (except for length) and compared to the RPL model the difference in WTP estimates between rural and urban respondents is substantially reduced.

Estimating the welfare effects of changes in the quality or supply of environmental goods is a key objective of many environmental/recreational studies. For this reason we therefore consider the implications for welfare estimation of failing to accommodate processing strategies relating to labelled alternatives. Specifically, we focus on four separate policy scenarios, one for each of the walk types. For these estimations we use the Hicksian welfare measure for the provision of each of these walk types *vis-à-vis* no walk (i.e., stay at home). For each policy scenario the walk is described as being between 1–2 hours duration, with car park facilities, fenced from livestock (in the cases of field and river walks only) and is paved with sign posting along the trail. All walks are specified as having a travel cost of €20, which represents a return trip distance of approximately 90 kilometres.

In Fig. 2 we compare the histograms of welfare change for the four policy scenarios across the various model specifications. Firstly, we note that all four policy scenarios are associated with an improvement in welfare. Comparing the welfare distributions attained from the four model specifications reveals stark differences. In particular the shape of the distributions of welfare estimates changes as one progresses from the MNL model to the RPL-DM model. The distribution attained under the MNL model reflects the underlying assumption of homogeneity in preferences and processing, whereas the remaining distributions show the heterogeneity in preferences and/or processing. The distributions of the conditional mean welfare estimates for the four policy scenarios are most dispersed under the RPL model, whereas those predicted under the DM and RPL-DM model are much tighter and have a more pronounced bi-modal distribution. These bimodal distributions are a consequence of the non-parametric discrete mixtures specification used to accommodate the heterogeneity in processing strategies. Importantly, the fact that the distributions attained are shown to be markedly different from those uncovered from the RPL and DM models provides further evidence of confounding between preference and processing heterogeneity, and the important role of failing to account for processing strategies in prediction of exteme taste sensities (i.e., outliers) (see Campbell et al., 2010, for a further discussion). Irrespective of model specification, we observe highest welfare estimates for the River walk (Fig. 2(d)) policy scenario, lowest for the Bog walk (Fig. 2(b)), with the Hill (Fig. 2(a)) and Field (Fig. 2(c)) walk scenarios ranking in-between. Nevertheless, we do find differences in the averages between model specifications. For instance, for the River policy scenario the mean welfare per trip estimate shifts from almost €40 under the MNL model to almost €55 under the RPL model and then to approximately €10 under both the DM and RPL-DM models.

Figure 2 about here.

Continuing with our comparisons along the rural-urban gradient, we separate the distributions for rural and urban respondents. In line with findings reported in Table 2, we remark that there appears to be a higher density of rural respondents with lower welfare values. Indeed, for all policy scenarios regardless of model specification used to address preference and/or processing heterogeneity, we find that the conditional means for rural respondent are on average lower than those derived for urban respondents. Most notably, the welfare estimates obtained for the Field and River policy scenarios are approximately 20 percent lower for rural respondents under all three non-MNL model specifications.

5 Discussion and conclusions

This paper examined the consequences of respondent's choosing their preferred recreational site on the basis of its name only in a DCE. The use of DCEs to model preferences for recreational goods is growing in application in the environmental economics literature. Typically this analysis assumes compliance with the continuity axiom of unlimited substitution between the recreational site attributes and the alternative recreational sites. For this condition to hold, respondents are assumed to consider and make trade-offs between every attribute across alternatives. However, there is growing evidence across a range of market and non-market goods to suggest that this assumption may be inappropriate. Indeed, there is empirical evidence showing that respondents often adopt heuristics when choosing their preferred alternative in the valuation tasks. One such heuristic which is the focus of this paper, is the adoption of attribute non-attendance in the presence of labelled alternatives.

This paper employed a DM approach to accommodate respondents who do not attend to the attributes described under one or more of the site alternatives. Specifically, the modelling approach enabled probabilistic determination of whether or not a respondent made their decision solely on the basis of the site's name, disregarding all other information associated with that alternative. Results from the analysis suggested that a sizeable proportion of respondents reached their decision by ignoring the attributes and focused only on the name of the alternative. The results from the models indicated that respondents were more likely to concentrate only on the alternative name for alternatives they had a higher preference for. In addition, results from our RPL-DM model, which simultaneously addressed both preference and processing heterogeneity, uncovered a substantially smaller degree of unobserved taste variation than our RPL model. This raises the concern of confounding between variations in taste and processing and that the standard, and widely used, models for accommodating random taste heterogeneity may be over estimating the extent of preference heterogeneity in datasets where processing heterogeneity may be an issue.

This paper also retrieved the conditional probability estimates to explore factors that contributed to processing strategies. Principally, the paper examined if rural and urban respondents processed information differently. The results revealed that a higher proportion of urban respondents had a propensity to consider only the name of the recreational alternative when they reached their choice outcomes. In addition, the differences emerged between the different walk alternatives. For example, there was a much larger proportion of urban respondents who were estimated to ignore the attributes of river and field walks compared to their rural counterparts. For the hill and bog walks, the difference between rural and urban respondents was much lower, albeit a higher proportion of urban respondents were also estimated to ignore the attributes for these alternatives.

It was further shown that accounting for processing strategies led to a general downward shift in marginal WTP for the attributes as well as for the estimates of overall consumer surplus. The largest impact on marginal WTP was for the shorter length attribute which was significantly lower from the MNL and RPL models. This suggests that the MNL and RPL models were overestimating the extent to which respondents' preferred shorter walks. In terms of the retrieved conditional consumer surplus estimates, it was illustrated that accounting for processing strategies had a large impact both on the estimated mean values for the walks as well as the overall distribution of consumer surplus. As a result, there was a large downward shift on estimated mean values as well as on the degree of dispersion of welfare related to the four policy scenarios considered in this paper.

Our findings have clear implications; from a methodological viewpoint, the results showed that there is a sizeable number of respondents choosing alternatives based on its name only—a phenomenon that has not be explored in much detail to date in the literature. While we acknowledge that these results are specific to this empirical case-study, our results do raise interesting issues associated with labels for DCEs. This is not an argument against the use of labelled experiments, since in many settings they are likely to be the correct mechanism to model realistic choices. Indeed labelled alternatives can be particularly useful for determining recreational site choice (Blamey et al., 2000). However, as shown in this empirical case-study the labels may have a proportionally larger impact upon respondents' choices than anticipated by researchers. From a policy perspective, failure to account for such processing strategies related to the alternatives could lead to erroneous welfare conclusions.

In the context of choosing farmland recreational walking trails, it is evident from this study that Irish residents on the whole prefer walks of shorter duration. This would suggest that policy-makers should be focused towards the development of these shorter length walks on farmland to meet preferences for the general Irish public. In terms of developing infrastructure at the walks, findings from this study indicated that Irish residents' value farmland walks that have a path and signage most highly, followed by walks that have a car-park and lastly by walks that are fenced-off from livestock. It is also apparent that of the types of farmland walks, river walks are most preferred and bog walks are least preferred, with field and hill walks having a similar impact upon preferences. Finally, it was evident that differences in processing strategies between rural and urban respondents further manifested themselves in differences in welfare estimates. On average, urban respondents had a higher WTP for the attributes of farmland walking trails as well as on the estimates of overall consumer surplus compared to rural residents.

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Table 1: MNL, RPL, DM and RPL-DM model results

		MNL		RPL		DM		RPL-DM	
		est.	|t-rat.|	est.	|t-rat.|	est.	|t-rat.|	est.	|t-rat.|
Duration (up to 2 hours)	μ	0.591	15.23	0.887	11.25	0.866	14.56	1.184	8.58
	σ			1.360	17.39			1.991	13.38
Car Park	μ	0.205	5.39	0.169	3.24	0.531	9.01	0.761	8.61
	σ			0.619	9.55			0.861	8.11
Fence	μ	0.136	2.87	0.102	1.55	0.409	6.36	0.609	6.88
	σ			0.760	10.22			0.609	3.92
Path and Signage	μ	0.326	7.58	0.333	4.75	0.73	12.16	1.055	9.82
	σ			1.070	15.87			1.445	12.47
Travel Cost	β	-0.027	26.12	-0.034	27.41	-0.091	19.37	-0.125	16.45
Hill walks	C	0.392	6.22	0.713	9.93	1.621	15.63	1.707	15.96
Bog walks	C	-0.134	1.95	0.115	1.49	1.322	8.57	1.203	6.87
Field walks	C	0.343	5.11	0.655	8.57	1.569	14.68	1.615	13.83
River walks	C	0.808	12.58	1.251	16.88	1.866	20.94	1.997	20.99
Ignore attributes of Hill walk	π_{δ^0}					0.258	10.67	0.237	10.21
Ignore attributes of Bog walks	π_{δ^0}					0.122	6.21	0.110	5.49
Ignore attributes of Field walks	π_{δ^0}					0.244	10.13	0.241	9.87
Ignore attributes of River walks	π_{δ^0}					0.372	14.86	0.364	14.59
$\mathcal{L}(\hat{\beta})$		-6876.196		-6254.446		-6126.549		-5638.272	
AIC/N		2.442		2.222		2.178		2.005	
BIC/N		2.452		2.237		2.263		2.025	
$\bar{\rho}^2$		0.101		0.184		0.198		0.262	
K		9		13		13		17	

Table 2: Comparision of marginal WTP per trip estimates (€)

			MNL	RPL[a]	DM[a]	RPL-DM[a]
Duration	All	Mean	21.79	19.41	9.17	8.08
		Std. dev.	-	34.23	1.45	12.05
	Rural	Mean	21.79	24.66	9.31	8.88
		Std. dev.	-	34.28	1.15	12.43
	Urban	Mean	21.79	11.69	8.97	6.88
		Std. dev.	-	32.71	1.79	11.38
Car Park	All	Mean	7.56	8.00	5.61	6.80
		Std. dev.	-	11.19	0.89	3.66
	Rural	Mean	7.56	6.16	5.69	6.14
		Std. dev.	-	10.99	0.70	3.70
	Urban	Mean	7.56	10.73	5.49	7.79
		Std. dev.	-	10.94	1.09	3.38
Fence	All	Mean	5.04	5.31	4.33	4.88
		Std. dev.	-	14.28	0.68	1.78
	Rural	Mean	5.04	2.17	4.39	4.78
		Std. dev.	-	11.97	0.54	1.77
	Urban	Mean	5.04	9.99	4.23	5.02
		Std. dev.	-	16.09	0.84	1.80
Path and Signage	All	Mean	12.04	17.69	7.72	10.21
		Std. dev.	-	23.62	1.22	7.87
	Rural	Mean	12.04	12.26	7.84	8.91
		Std. dev.	-	22.73	0.97	7.59
	Urban	Mean	12.04	25.77	7.56	12.14
		Std. dev.	-	22.63	1.51	7.91

[a] Calculated from the means of the conditional distributions.

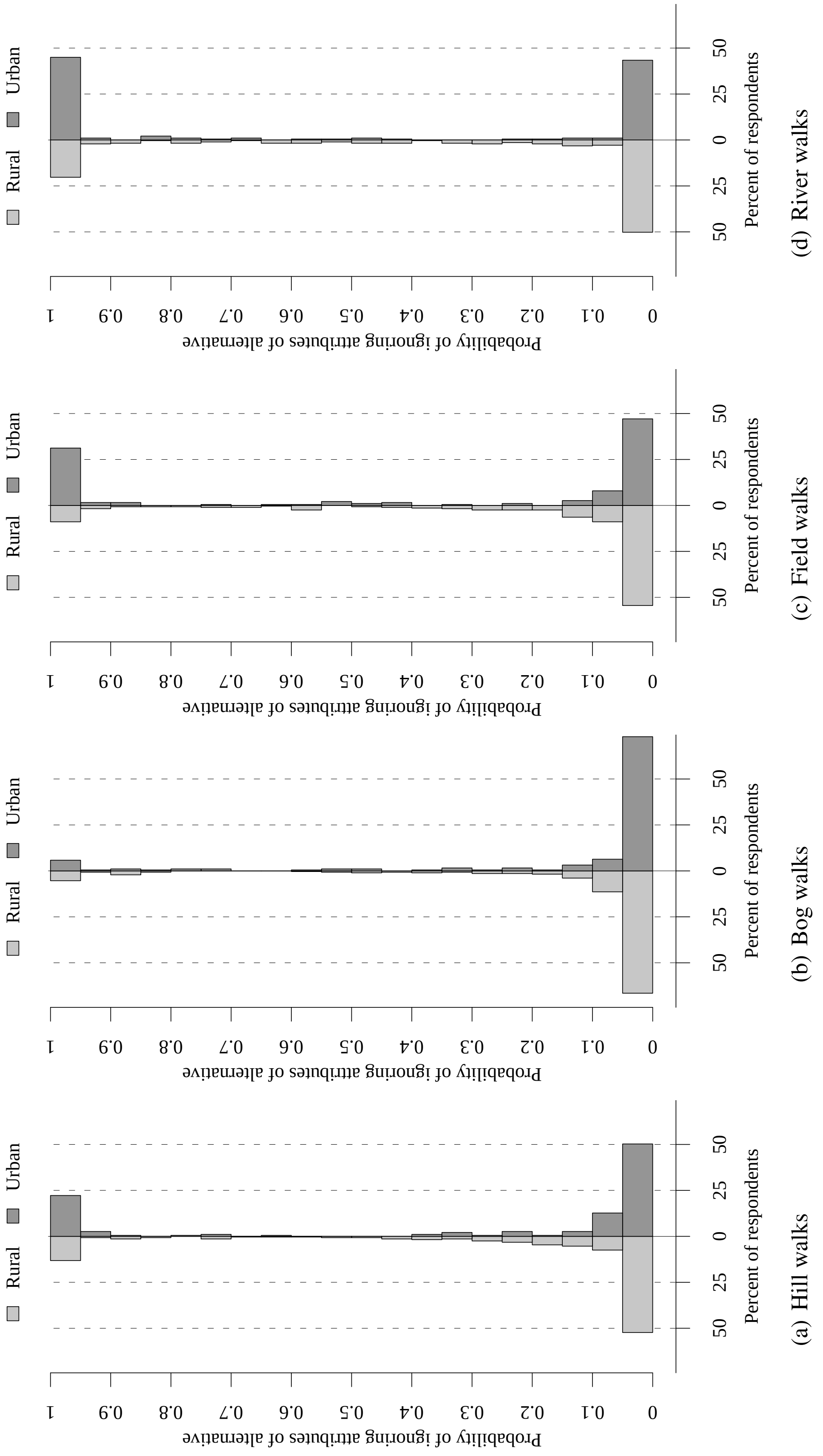
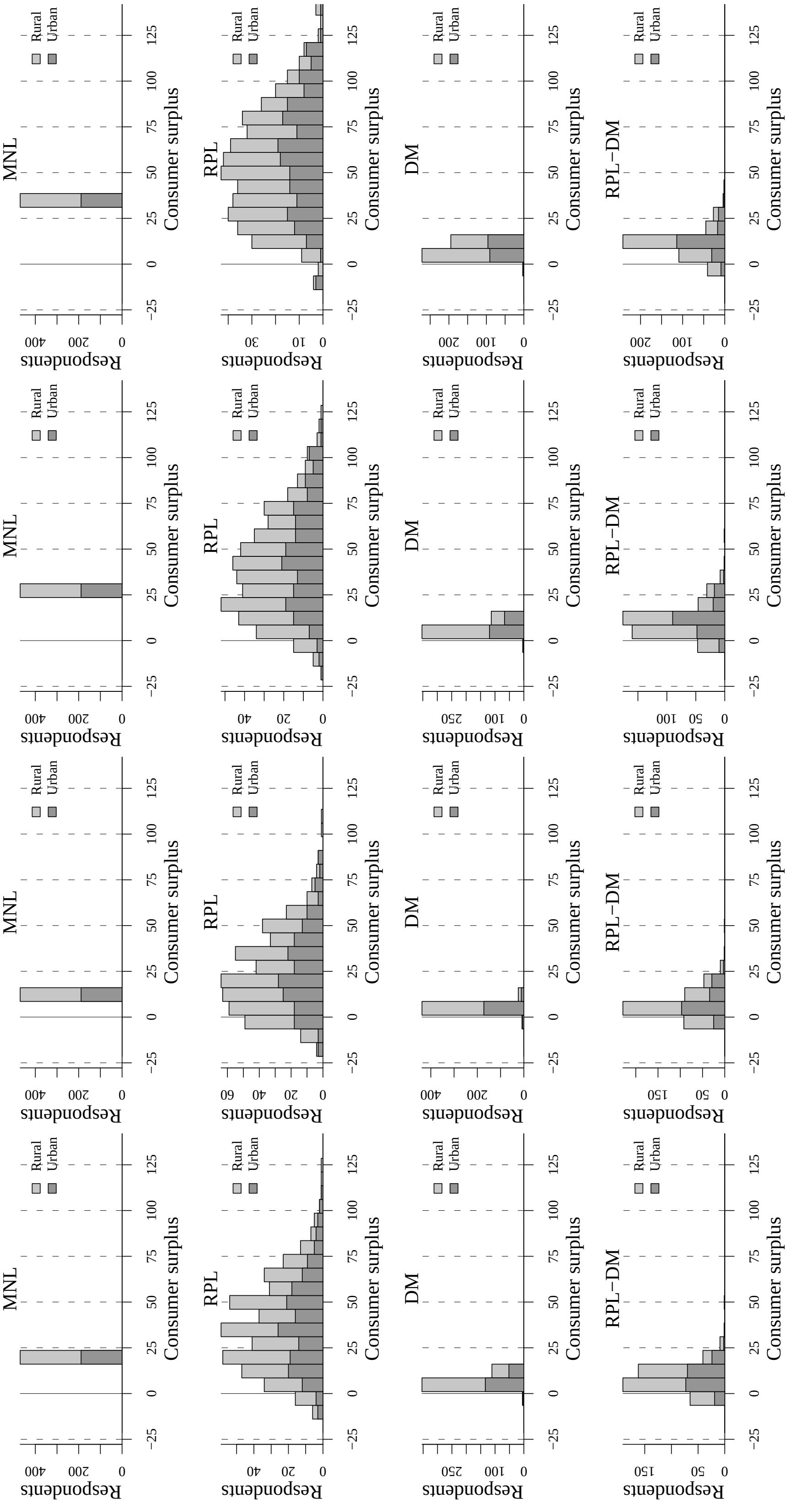


Figure 1: Conditional distributions of ignoring attributes of alternatives for rural and urban respondents



(a) Hill walks
(b) Bog walks
(c) Field walks
(d) River walks

Figure 2: Conditional distributions of consumer surplus per trip for rural and urban respondents (€)