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Labelling effects in discrete choice experiments

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Labelling effects in discrete choice experiments

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, this paper exploits a discrete mixtures approach that also encompasses continuous distributions to reflect the heterogeneity in preferences for the attributes. We find evidence that a proportion of respondents adopt this processing strategy and that the strategies employed by rural and urban respondents are somewhat different. Results further highlight that model fit and measures of welfare are sensitive to assumptions related to processing strategies among respondents.

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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. In the environmental economics literature, labels usually refer to sites, locations, policy names or other descriptors and the labels usually communicate information regarding the tangible or intangible qualities of the alternatives (Blamey et al., 2000). 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. In fact, using labels in a DCE is perhaps more reflective of actual decision making given that many marketed goods are sold under labels (or brands). 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; Bjorner et al., 2004) and that consumers may have preferences for the label over the physical characteristics of the good. 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, instead depends upon the respondent's perception of that good. As outlined in Czajkowski and Hanley (2009), this notion also has parallels with the notion of framing dependence suggested by Kahneman and Tversky (2000), whereby the label reflects the manner in which the good is framed to the respondent and is different from the good's attributes. Moreover, within the context of recreational site choice, which is the focus of this study, 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 invokes memories of past fond experiences (Blamey et al., 2000). Labelling alternatives enables these factors to be captured more accurately. On the other hand, 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 resource allocation decisions. 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 the 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; **?**).

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 non-attendance of attributes as a consequence of the alternative's label. This is in spite of the fact that labelled alternatives are commonly used in stated preference studies and that results in Blamey et al. (2000) and De Bekker-Grob et al. (2010) highlight that respondents have a higher propensity to ignore attributes when labelled alternatives are included in the choice experiment. For example, Blamey et al. (2000) found that the inclusion of labels reduced the attention respondents gave to the physical attributes of a good and caused a reallocation of utility away from the part-worths for these attributes and towards a value for the label itself. While not addressing the impact of labels on non-attendance, it is worth mentioning that Czajkowski and Hanley (2009) found that controlling for the value of the label (in their case national park designation) increased the scope sensitivity of the welfare estimates. In this current study we provide an in-depth analysis to probabilistically determine for each alternative, the proportion of respondents who made their choices based on its label only. As a result, our paper adds to the small, but growing, literature exploring labelling influences in DCEs.

Second, we use 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., Campbell et al., 2008; 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., Scarpa et al., 2009; Hensher et al., 2010; Campbell et al., 2011) 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). In this paper, we use 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 any great 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. In this paper we investigate differences in processing across a rural-urban gradient. The reason for focusing on rural-urban differences is that in the context of 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 whereby rural and urban respondents' perceptions of farmland walking trails appeared to be different. 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). Furthermore, in the context of Irish residents, both Hynes et al. (2011) and Campbell et al. (2009) find differences in preferences for countryside landscape features between rural and urban residents. In this study, we determine whether differences may also exist in the processing strategies along the rural-urban gradient. We extend our analysis and also 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 exploration adds to the literature examining rural-urban differences in recreational preferences.

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. There are also differences in the extent of processing strategies between different types of recreational walks. We also find this phenomenon is more prevalent among respondents residing in urban areas compared to those residing in rural areas. 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 these types of 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

2.1 Model specifications

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:

$$\begin{aligned} U_{nj_t} &= \beta x_{nj_t} + C_j + \varepsilon_{nj_t} \\ &\vdots \\ U_{nJ_t} &= \beta x_{nJ_t} + C_J + \varepsilon_{nJ_t}, \end{aligned} \tag{1}$$

where β_J are parameters to be estimated, C_J 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 do not vary as a result of unobserved factors. While in many cases this assumption may hold, a growing number of empirical studies have shown that there is often unobserved 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. 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:

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

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 [1]. 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:

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

where C and C^* respectively represent the alternative specific constant for respondents who attend to the attributes associated with alternative j and those who do not attend to its attributes. We specify each of the discrete variables (δ) as a dummy variable, as follows:

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

[1] We acknowledge the similarity between DM and latent class logit models, which also assume finite representations of heterogeneity. In fact, DM and latent class logit models are formally equivalent, the main difference being that in DM models the focus is usually on segmenting on a per parameter basis and not on the basis of the full set of parameters, which is typically the case in latent class models.

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:

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

where $s = 1, \ldots, S$ is an index over all possible combinations of the J dummy variables (i.e., $S = 2^J$). As an example with two alternatives, we would have $S = 4$, as follows:

$$S = \begin{cases} s_1 \text{ relates to the case where } \omega_1 = \left(\pi_1^1, \pi_2^1\right) \text{ and } \gamma_1 = \left(\delta_1^1, \delta_2^1\right); \\ s_2 \text{ relates to the case where } \omega_2 = \left(\pi_1^1, \pi_2^0\right) \text{ and } \gamma_2 = \left(\delta_1^1, \delta_2^0\right); \\ s_3 \text{ relates to the case where } \omega_3 = \left(\pi_1^0, \pi_2^1\right) \text{ and } \gamma_3 = \left(\delta_1^0, \delta_2^1\right); \\ s_4 \text{ relates to the case where } \omega_4 = \left(\pi_1^0, \pi_2^0\right) \text{ and } \gamma_4 = \left(\delta_1^0, \delta_2^0\right). \end{cases} \tag{8}$$

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 and the label associated with 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 the probability that the attributes and label was considered for alternative j, 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. The appeal of this approach is that is possible to isolate respondents who considered only the name of the alternative when reaching their choice outcomes while concurrently obtaining attribute coefficients for those respondents who did attend to the attributes.[2]

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:

$$\Pr\left(y_n|\delta,\Omega,x_n\right)=\sum_{s=1}^{S}\omega_s\int_{\beta}\prod_{t=1}^{T_n}\frac{\exp\left(\delta_j(\beta x_{njt}+C_j)+\left(1-\delta_j\right)C_j^*\right)}{\sum_{j=1}^{J}\exp\left(\delta_J(\beta x_{nJt}+C_J)+(1-\delta_J)\,C_J^*\right)}f\left(\beta|\Omega\right)d\beta. \tag{9}$$

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 (9)), 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 (9) cannot be calculated exactly (because the inte-

[2] We acknowledge that there may be a range of other processing strategies that will not be captured under this specification. While the specification could be constructed to also explore these patterns of processing, doing so goes beyond the focus of the present paper and risks distracting from the processing associated specifically from the labelled alternative.

grals do not have a closed form solution), we estimate these models by simulating the log-likelihood using 250 Halton draws.

2.2 Conditional distribution estimation

While the RPL, DM and RPL-DM models facilitate taste variation and/or processing strategies 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:

$$L(\theta|y_n) = \frac{L(y_n|\theta) f(\theta)}{\int\limits_{\theta} L(y_n|\theta) f(\theta) d\theta}, \tag{10}$$

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.[3]

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

[3]We fully acknowledge the fact 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.

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 and previous Irish studies exploring preferences for countryside features (e.g., Hynes et al., 2011; Campbell et al., 2009). 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.

2.3 Welfare estimation

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 $\beta_\$$ 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:

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

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:

$$\text{CV} = \int_{\theta} \frac{1}{-\beta_{\$}} \left[\ln\left(\sum_{j=1}^{J} \exp\left(V_j^1\right) \right) - \ln\left(\sum_{j=1}^{J} \exp\left(V_j^0\right) \right) \right] f(\theta)\, d\theta. \tag{12}$$

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.

For the study we sought to establish which would be the most appropriate methodology to recover the economic values associated with the provision of farmland walking trails. Given the nature of this study (population level) and the fact that there are limited established farmland walking trails currently in Ireland for which to conduct a revealed travel cost study, a DCE was deemed most suitable for the research objectives since it captures multiple trade-offs across a range of different attributes and alternatives.

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.

After extensive discussions with key stakeholders and as well from discussions with focus group participants, it was decided to use the labels to reflect the diversity of farmland in Ireland, and, hence, the potential for diverse types of farmland walking trails. As a result, the labels reflected the main types of potential farmland walks that could be implemented at a national level namely, Hill, Bog, Field and River walks. Therefore, when the walks were described to respondents completing the choice tasks they were described as for example, as a Hill walk with certain features described by the attributes and their levels. In addition, a description of the difference between the types of walks was given. This included information of the differences between the types of terrain that the walks traversed as well as a description of each of the walk alternatives.

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. Care was also taken when designing the DCE to ensure that the attributes chosen for the study were realistic for the labels used to describe the walk alternatives (i.e., to ensure that respondents could associate the attributes with the labels used to describe the alternative walks). This was pretested during focus group discussions as well as one-to-one interviews. Questions were also included in the pilot and main questionnaires to explore respondents' acceptance of the choice scenarios presented to them.

The first attribute, 'Length', indicated the length of time needed to complete the walk from start to finish (all walks were described as looped (circular) so that people using the walks did not have to walk back along the same route). 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. The levels of the Length attribute were presented using interval levels to reflect the fact that not everyone walks at the same pace. 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. This attribute only applied to the field and river walk alternatives, since these are the most likely types of walks that livestock would be encountered. 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 one-way distance (in kilometres) that the walk is located from the respondent's home. The attribute was presented with six levels (5, 10, 20, 40, 80 and 160 kilometres) reflecting realistic distances that would be travelled in Ireland for a recreational day trip. 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 conceptually realistic and acceptable payment mechanism. Other choice experiments that explore recreational choices have also successfully used this approach including Adamowicz et al. (1994), Hanley et al. (2002) and Christie et al. (2007).

The available alternatives that were present in each choice task varied. An example of a choice task used for the DCE is given in Figure 1. Hence, as can be shown, in this instance the hill walk alternative is not available and respondents would have been asked to choose between the other options. The

	Bog walk	Field walk	River walk	Choose none
Length	3-4 hours	1-2 hours	1-2 hours	
Car Park	Yes	No	No	I would not choose any of the walks. I would stay at home.
Fence	–	No	Yes	
Path and Signage	Yes	No	Yes	
Distance	40 km	10 km	80 km	

Fig. 1: Example Choice Card

rotation was used to ensure that the processing strategies were not associated with obvious ordering effects. In addition, the rotation ensured that the labelling effects could be isolated for each alternative.

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 references cited therein). Our design comprised of a panel of twelve choice tasks. For each task, respondents were asked to choose between a combination of 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. Broadly in line with the population breakdown, the sample consisted of 52 percent females and on average were just over 40 years of age. Just over one-fifth of respondents stated they had obtained a university qualification. Of the 63 percent of respondents who did disclose their income, the average annual income was approximately €28,500.

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[4], 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.

For the RPL model we specify all the non-cost attributes as having Normal distributions since it is possible that preferences for these attributes may span the distribution including both the negative and positive preference domains. For example, for the fence attribute some respondents may like a fence for fear of livestock, while other respondents may find that a fence along the walking trail restrictive. Similarly, while 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.[5] 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

[4]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.

[5]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.

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.$\|$
Length (up to 2 hours)	μ	0.591	15.23	0.887	11.25	0.986	16.14	-1.443	10.39
	σ			1.360	17.39			2.098	13.98
Car Park	μ	0.205	5.39	0.169	3.24	0.411	6.83	0.523	5.70
	σ			0.619	9.55			1.004	9.03
Fence	μ	0.136	2.87	0.102	1.55	0.211	2.81	0.260	2.53
	σ			0.760	10.22			0.774	4.24
Path and Signage	μ	0.326	7.58	0.333	4.75	0.438	6.28	0.558	4.71
	σ			1.070	15.87			1.515	13.71
Travel Cost	β	-0.027	26.12	-0.034	27.41	-0.105	17.63	-0.161	15.81
Hill walks	C	0.392	6.22	0.713	9.93	0.684	6.44	1.125	9.006
	C^*					1.638	15.53	1.745	16.09
Bog walks	C	-0.134	1.95	0.115	1.49	0.427	4.02	0.818	6.61
	C^*					1.226	7.91	1.134	6.59
Field walks	C	0.343	5.11	0.655	8.57	0.698	6.25	1.196	8.91
	C^*					1.552	14.38	1.589	14.35
River walks	C	0.808	12.58	1.251	16.88	0.859	7.75	1.632	1.91
	C^*					1.888	20.88	2.041	20.99
Ignore attributes of Hill walk	π_{δ^0}					0.245	10.15	0.225	9.95
Ignore attributes of Bog walks	π_{δ^0}					0.136	6.32	0.127	5.49
Ignore attributes of Field walks	π_{δ^0}					0.243	10.00	0.244	9.87
Ignore attributes of River walks	π_{δ^0}					0.357	14.28	0.345	14.59
$\mathcal{L}(\hat{\beta})$		-6876.196		-6254.446		-6092.486		-5549.466	
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		17		21	

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 36 percent of respondents are estimated to ignore the attributes of river walks and consider only its name, compared to approximately 14 percent for the attributes of a bog walk and approximately 24 percent for the attributes of hill and field walks respectively.

Turning our attention to the alternative specific constants retrieved from respondents who are predicted as having attended to the alternative's label *and* attributes, we note that they are all significant. However, as would be expected, these are to be of a much smaller magnitude than the constants uncovered from respondents who are predicted as having only considered the alternative's label, which are also found to be significant. The fact that the constants estimated for the share of respondents who only consider the alternatives labels are of a relatively large magnitude suggests that respondents only ignored the attributes of the walks that they were most favourably disposed to. This is also reflected by the fact that the implied rank of these constants are in line with the ordering of the predicted probabilities of attribute non-attendance of certain walk alternatives (i.e., river walk is estimated as the most preferred walk type and the highest proportion of respondents are estimated to ignore its attributes).

With regard to the attribute coefficients, which are fixed in this model, 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 resulting from the alternative's name. This specification is associated with a huge improvement in model fit from the RPL and DM models (an improvement of 705 and 543 log-likelihood units respectively). Notice also that, the $\bar{\rho}^2$, AIC and BIC statistics[6] 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 inferences can be made from the coefficients representing the alternative specific constants. 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. This suggests that model specifications that only uncover unobserved taste heterogeneity may (hugely) overestimate the extent of the heterogeneity if possible processing strategies are not accounted for in estimation.

4.2 Rural-urban comparison of processing strategies

As previously noted, a major interest in this paper is to determine whether respondents residing in rural and urban locations exhibit differences in processing strategies related to alternative farmland

[6]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.

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 complete set of attributes within each of the four walk alternatives were not attended to, which we separate along a rural-urban gradient[7]. The distributions of the retrieved conditional mean probabilities from the RPL-DM are summarised in Fig. 2.

An examination of the back-to-back histograms in Fig. 2 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. 2(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. 2(c)). We also observe that a slightly higher proportion of urban respondents are predicted to ignore the attributes of Hill walks (Fig. 2(a)). The attributes of the Bog walk (Fig. 2(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.

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

[7]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. The sample breakdown is 281 and 189 rural and urban respondents respectively.

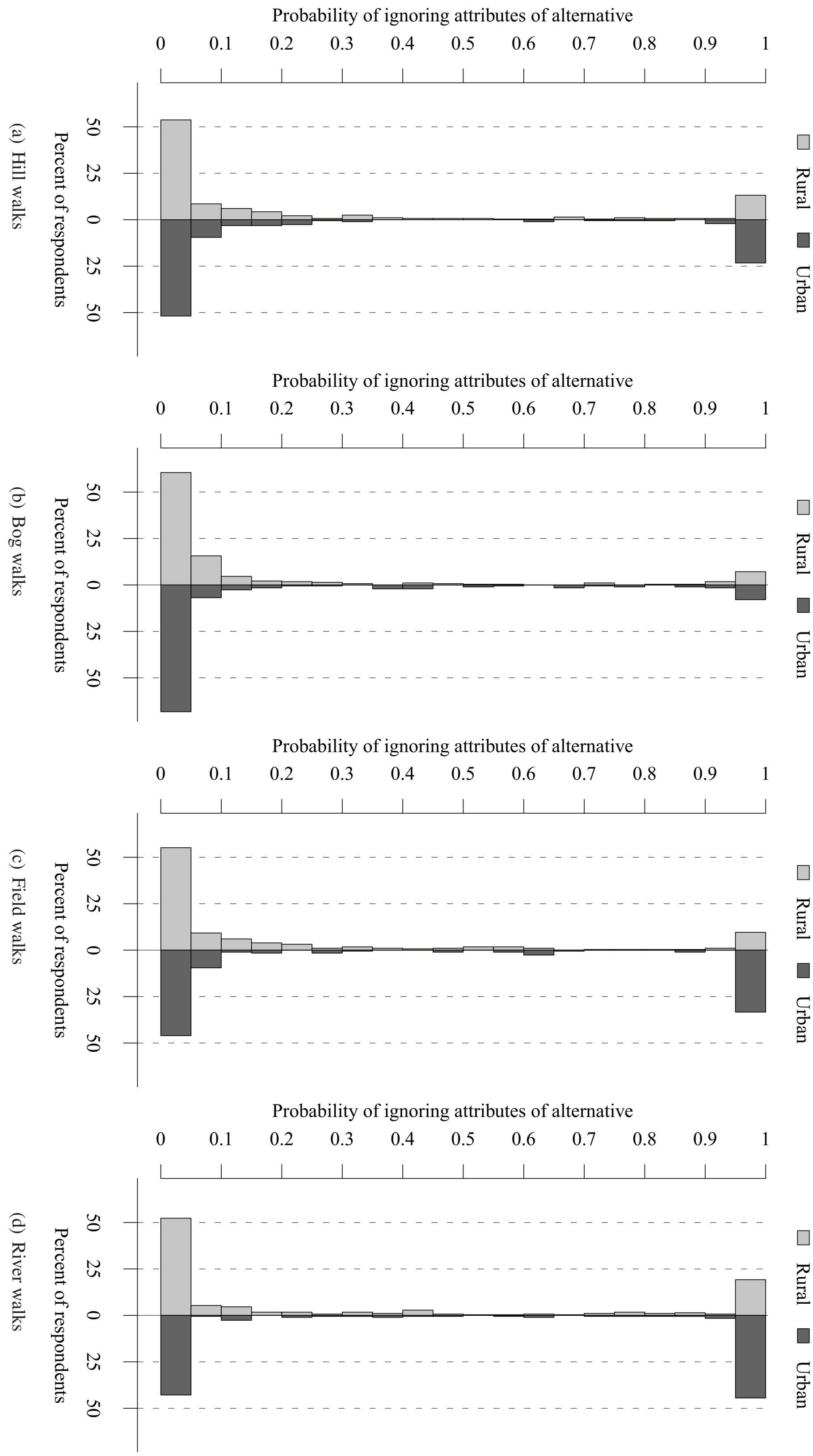

Fig. 2: Conditional distributions of ignoring attributes of alternatives for rural and urban respondents

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.

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 attained from the distribution of conditional 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 excep-

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

			MNL	RPL[a]	DM[a]	RPL-DM[a]
Length	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.

tion 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 mean marginal WTP per trip estimates produced from the conditional means 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 conditional means uncovered 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 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).[8]. 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. 3 we compare the histograms of the means of the conditional distributions 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 bi-modal distributions are a consequence of the non-parametric discrete mixtures specification used to accommodate the heterogeneity in processing strategies.

[8]While Hicksian welfare measures could have calculated for a range of different policy scenarios, we focus on the welfare associated with providing one of the walk alternatives *versus* having no walk, as this should more easily enable policy-makers prioritise their decisions between the different types of farmland walks

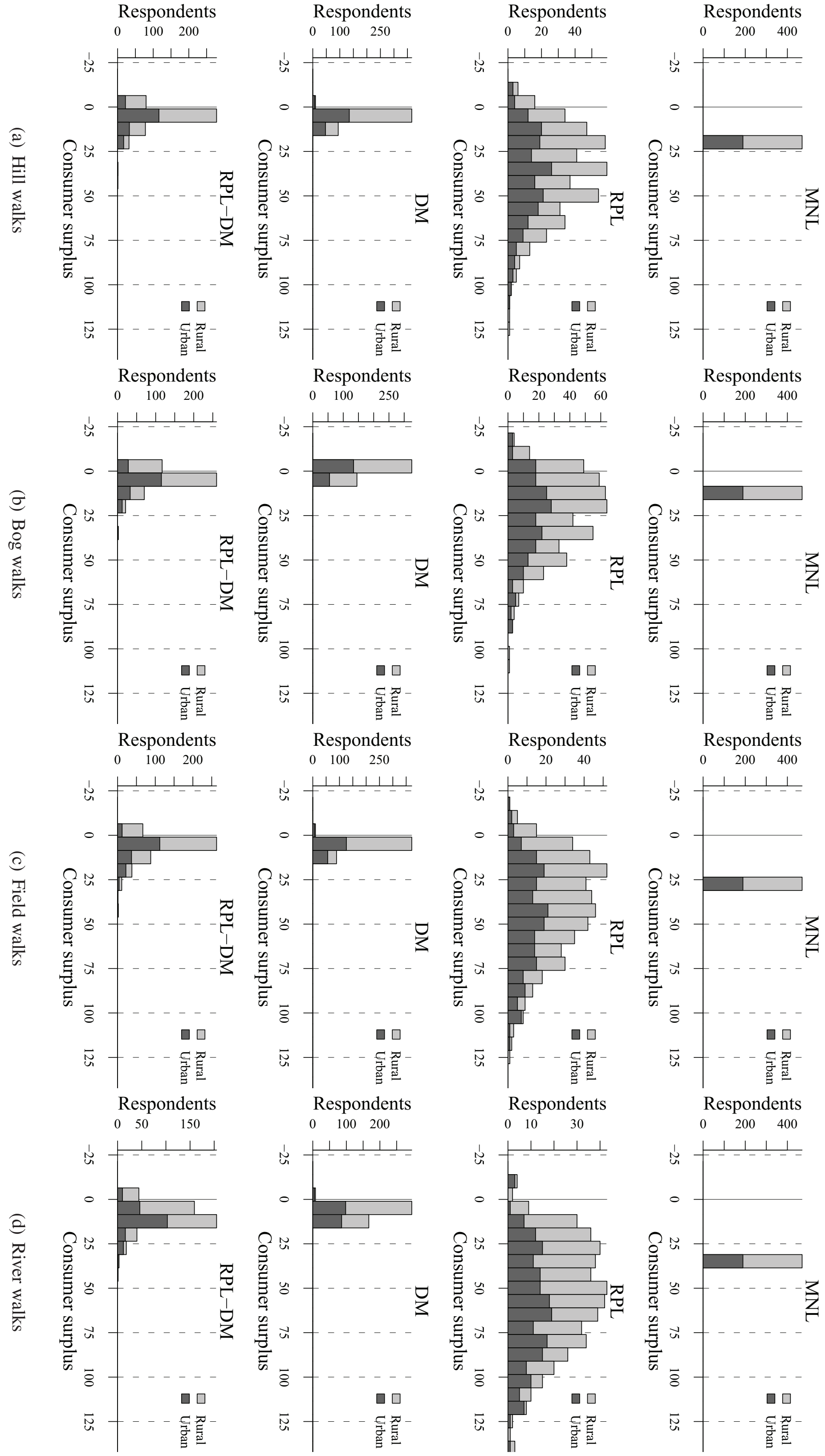

Fig. 3: Conditional distributions of consumer surplus per trip for rural and urban respondents (€)

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. Irrespective of model specification, we observe highest welfare estimates for the River walk (Fig. 3(d)) policy scenario, lowest for the Bog walk (Fig. 3(b)), with the Hill (Fig. 3(a)) and Field (Fig. 3(c)) walk scenarios ranking in-between. Nevertheless, we do find differences in the averages associated with these distributions 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 less than €10 under both the DM and RPL-DM models.

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 means of the conditional means retrieved for rural respondents are always 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. Moreover, results uncovered from our final RPL-DM model suggest that the means of the distributions of welfare changes associated with each policy scenario are all over 20 percent higher, and even extending to over 30 percent higher in the case of the Bog policy scenario.

5 Discussion and conclusions

This paper examined the consequences of respondents choosing their preferred recreational site only on the basis of its name in a DCE. 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 respondent's were more likely to concentrate only on the alternative name for alternatives they had a higher preference for. Further findings from the study showed that 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 whether 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 were 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 the use of labels in 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. Our results also highlight the need to accommodate both preference heterogeneity and processing strategies (simultaneously) to properly determine what factors may be influencing respondents' choices. Furthermore, policy conclusions are sensitive to the inclusion of both and hence, only accommodating either preference heterogeneity or processing strategies can bias the resulting welfare estimates and lead to potentially inaccurate policy conclusions.

In the context of choosing farmland recreational walking trails, 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. It is also 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. . 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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