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Exploring cost heterogeneity in recreational demand

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Abstract

Farmland can confer significant public good benefits to society aside from its role in agricultural production. In this paper we investigate preferences of rural residents for the use of farmland as a recreational resource. In particular we use the choice experiment method to determine preferences for the development of farmland walking trails. Our modelling approach is to use a series of mixed logit models to assess the impact of alternative distributional assumptions for the cost coefficient on the welfare estimates associated with the provision of the trails. Our results reveal that using a mixture of discrete and continuous distributions to represent cost heterogeneity leads to a better model fit and lowest welfare estimates. Our results further reveal that Irish rural residents show positive preferences for the development of farmland walking trails in the Irish countryside.

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1 Introduction

Farmland produces a wide range of private and public goods and services for society. Many of the private benefits of farmland arise from the production of food and fibre and other consumable goods that are exchanged in formal markets. Value is determined in these markets through exchange and quantified in terms of price. On the other hand, environmental services and recreational benefits produced by farmland create a range of public good benefits. Declining agricultural activity coupled with policy emphasis on enhancing the public good provision of farmland has led to a greater emphasis being placed on providing the non-market benefits from farmland. Indeed, in Ireland, research has shown that Irish farmland produces substantial non-market benefits, in addition to the traditional role of agricultural production (Campbell, 2007; Hynes et al., 2011). In particular, the role of farmland as a recreational resource is increasingly being recognised within Ireland (Buckley et al., 2009a) and beyond (Fleischer and Tsur, 2000). In this context, this paper seeks to investigate Irish rural residents' preferences for the provision of recreational walking trails on farmland.

There are a number of reasons for focusing on the demand for recreational walking. First, among the general population of Ireland, walking is by far the most common recreational activity. A study by Curtis and Williams (2005) found that three-quarters of the Irish adult population participated in walking for recreational purposes. Second, given the popularity of recreational walking, there is a considerable body of evidence to suggest that walking activity has the potential to generate significant revenue from both tourists and domestic residents (Failte, 2009; Fitzpatrick and Associates, 2005). For instance Fitzpatrick and Associates (2005) estimated the direct expenditure, such as food and accommodation expenditure, of recreational trails and forest recreation at €305 million annually while the non-market benefits value of trails were estimated at €95 million. Third, Ireland's most highly regarded walks are located in mostly rural regions of low population densities where local economies have been in stagnation due to the decline in agriculture (Buckley et al., 2008a). Buckley et al. (2008b) quantified the opportunity cost associated with recreation on farm commonage[1]. They found that only 23 percent of farms showed a positive gross margin in a post-decoupling scenario. They note that if the payment was removed the economics of farming activity on marginal areas is questionable.

Hynes et al. (2007) argue that relative to traditional agricultural activities, outdoor recreation may represent a more economically efficient use of commonage resources, albeit providing recreational access does not necessarily require farmers to stop commercial farming. They note that policy-makers are recognising the value of open-air outdoor recreational as a means of supporting rural in-

[1]Commonage refers to unenclosed land on which two or more farmers have pasture rights in common (Lyall, 2000)

comes and the Rural Development Plan through niche tourism; environmentally guided farming; rural diversification; job creation and rural regeneration. Therefore, increasing provision of walking trails on farmland could help maximise the potential of the recreational walking market as well as provide an alternative means to sustain marginal rural regions. Finally, previous research by Buckley et al. (2009a)—based on two farmland recreational sites in Connemara—found support among walkers for more formalised walking trails.

Ireland is a particularly unique case study to examine the recreational walking benefits of farmland. This is because the rights of access to the countryside belongs primarily to private landowners, who are mostly farmers. In this paper we investigate preferences for the development of farmland walking trails using the choice experiment (CE) method. CEs are a stated preference methodology widely used by practitioners in the field of environmental and resource economics to derive estimates of willingness to pay (WTP) for environmental non-market goods and services. The appeal of CEs lies in their ability to provide rich information on the preferences that individuals hold for environmental goods and services. Additionally a wide array of random utility models are available from which CE data can be analysed. In this paper we employ a variety of models that fall under the mixed logit umbrella. In particular we use various specifications of the random parameters logit (RPL) model, which has the ability to capture random taste variation.

For the RPL model, debate remains regarding how to appropriately accommodate random taste variation in estimation. In particular, what distributions should be employed to represent the random taste heterogeneity. For derivation of WTP from RPL models, two considerations are important. First, what distributions should be applied to the non-cost attributes representing a particular environmental service. Second, what distribution should be assumed for the coefficient representing the cost attribute. Balcome et al. (2009) explored many of these issues and found little support for fixing the cost coefficient, which to date, has been a relatively common practice in the literature (e.g., Colombo et al., 2007; Provencher and Bishop, 2004; Morey and Rossmann, 2008; Carlsson et al., 2007; Bujosa et al., 2010). Indeed, Thiene and Scarpa (2009) call the assumption of a fixed marginal utility of money across individuals, implied by a fixed cost coefficient, *heroic*.

The main reason why a fixed cost coefficient is assumed in the literature is because it has a number of convenient properties. For example, if the non-cost coefficients are specified with a Normal distribution, then the distribution of the mean and standard deviation of WTP is also Normal when the cost coefficient is fixed. Therefore a fixed coefficient allows computationally straightforward WTP estimates. A further reason why cost is held constant is that specifying it as random can lead to extreme (negative and positive) estimates for marginal WTP. Additionally, a model with a random cost attribute may not have well defined moments (Balcome et al., 2009; Daly et al., Forthcoming). However, as noted by Train and Weeks (2005) assuming a fixed cost coefficient implies that the standard deviation of unobserved utility (the scale parameter) is the same for all observations. Scarpa et al. (2008) note that in the context of recreational choice, which is also the focus of this study, if the travel cost coefficient is fixed when scale varies over observations then the variation in scale will be erroneously attributed to variation in WTP for site attributes.

In this paper we investigate alternative specifications for the travel cost coefficient in mixed logit models of recreational site-choice. We add to the literature by exploring heterogeneity in the cost coefficient between a discrete, continuous and a mixture of distributions (combining discrete and continuous distributions), where the latter specification can accommodate multi-modality in preferences. Other studies have explored the multi-modality of attribute heterogeneity (e.g., Wasi and Carson, 2011; Fosgerau and Hess, 2009; Fosgerau and Bierlaire, 2007; Scarpa et al., 2008). In this paper we concentrate on alternative specifications for cost only, as opposed to the non-cost attributes, given its paramount importance in welfare estimation. This mirrors an interest within the literature on how to represent the cost coefficient and obtain sensible WTP estimates. For instance, a log-normal distribution can ensure that the distribution of cost is bounded below zero, which ensures the theoretically plausible negative utility associated with cost, yet practical applications have shown that it can lead to unusually large and untenable WTP estimates (Train and Weeks, 2005). Furthermore, as shown by Scarpa et al. (2008) the undesirable skewness of WTP distributions derived from preference space model specifications based on random travel cost coefficients is not eliminated by assuming bounded distributions. On the other hand, a number of studies have shown that parametrising the model directly in WTP space provides estimates of WTP distributions that are more tenable and associated with less extreme WTP values (Sonnier et al., 2007; Train and Weeks, 2005; Scarpa et al., 2008; Balcome et al., 2009). As a result, in addition to our preference space specifications, we investigate the impact of using a mixture of distribution approach in WTP space, which to our knowledge, has not been previously examined within the literature. According to Daly et al. (Forthcoming) parametrising models directly in WTP space also ensures finite moments for the WTP distributions. A noteworthy study by Torres et al. (2011) using Monte Carlo simulation, found that mistaken assumptions about the cost parameter can amplify environmental attribute mis-specification. They find that this may be due to assuming a constant parameter on cost, rather than getting the distribution wrong, although they note that results are sensitive to the size of the environmental changes being valued.

The remainder of the paper is structured as follows. In the next section we explain our econometric methodology. This is followed by a description of the policy context for the research, survey design and implementation in section 3. Section 4 presents and discusses the results. Finally section 5 presents the conclusions and policy recommendations arising from our findings.

2 Methodology

2.0.1 Preference Space Models

In this paper we explore the implications of different distributional assumptions for the cost coefficient in mixed logit models. Starting with the conventional specification of utility for the RPL model, where respondents are indexed by n, chosen alternative by i in choice occasion t, the cost attribute by p and the vector of non-cost attributes by x, we have:

$$U_{nit} = -\alpha p_{nit} + \beta' x_{nit} + \eta_{nit} + \varepsilon_{nit}, \tag{1}$$

where p_{ni} and x_{ni} are the observed variables that relate to the cost and non-cost attributes respectively, $-\alpha$ and β represent the coefficients for the cost and non-cost attributes. η represents error components that induce correlations between the designed alternatives (Scarpa et al., 2005; Campbell, 2007; Scarpa et al., 2007). These are normally distributed with a zero mean and standard deviation (σ^2) so that $\eta \sim N(O, \sigma^2)$ where η_{nit} is equal to zero for the status quo alternative and ε is an *iid* Gumbel distributed error term. In the first model specification considered in this paper we assume a fixed cost coefficient. For this model we define θ to represent the combined vector of β and η so that the unconditional choice probability for the RPL model, with random continuous cost and non-cost attributes becomes.

$$\text{Prob}(y_n) = \int_\theta \prod_{t=1}^{T_n} \left(\frac{\exp(-\alpha p_{nit} + \beta' x_{nit} + \eta_{nit})}{\sum_j \exp(-\alpha p_{njt} + \beta' x_{njt} + \eta_{njt})} \right) f(\theta) d(\theta) \tag{2}$$

where y_n gives the sequence of choices over the T_n choice occasions for respondent n, i.e. $y_n = \langle i_{n1}, i_{n2}, \ldots, i_{nT_n} \rangle$.

A key element with the specification of random taste heterogeneity is the assumption regarding the distribution of each of the random parameters (Hensher and Greene, 2003). Random parameters can take a number of predefined functional forms, such as, for example, Log-Normal, Normal or Triangular. Additionally, more recent studies have gone beyond the assumption of unimodiality and allow for multimodality distributions. Examples include the mixtures of normals approach (e.g., Fosgerau and Hess, 2009; Wasi and Carson, 2011) or mixture of normals and log-normals (e.g., Fiebig et al., 2010; Hensher and Greene, 2011) or the Legendre Polynomial as used by Fosgerau and Bierlaire (2007) and Scarpa et al. (2008). Based on *a priori* expectations of the possible signs of the attributes, we specify the heterogeneity for all of the non-cost attributes as having a Normal distribution, $\beta \sim \mathcal{N}(\mu, \sigma)$, while we explore alternative specifications for the cost coefficient.

In our second model specification we assume that the cost coefficient is represented by two discrete values, rather than remain fixed. In estimation this is achieved by assigning α with m mass points, α_m, each of mass points is associated with a probability π_m, with the condition that the combined probabilities adds to one (Hess et al., 2007). In this case the unconditional choice probability takes the following form:

$$\text{Prob}(y_n) = \sum_{m=1}^{m} \pi_m \left[\int_\theta \prod_{t=1}^{T_n} \left(\frac{\exp(-\alpha_m p_{nit} + \beta' x_{nit} + \eta_{nit})}{\sum_j \exp(-\alpha_m p_{njt} + \beta' x_{njt} + \eta_{njt})} \right) f(\theta) d(\theta) \right] \tag{3}$$

In this model specification we segment the cost coefficient into two mass points, each with an associated probability, while the remaining attribute coefficients are each specified with a single continuous distribution. Using such a modelling approach represents somewhat of a hybrid between the RPL and latent class (LC) models. This is because we have specified our non-cost attributes to follow a continuous distribution as in the RPL model, while we have specified our cost attribute to be represented by two finite values each with association probabilities, which is common for LC models. The main difference between our specification and the LC model is that we segment on a per parameter basis (in this case based on the cost parameter) rather than on the basis of the full set of parameters which is typical in LC models.

Notwithstanding the ability of the discrete mixtures (DM) approach to capture some heterogeneity associated with the cost attribute, we also explore the potential of using a continuous distribution for cost, rather than assuming a fixed or DM representation. In this case we can extend θ to represent the combined vector of α, β and η so that the unconditional choice probability for the RPL model, with random continuous cost and non-cost attributes becomes

$$\text{Prob}(y_n) = \int_\theta \prod_{t=1}^{T_n} \left(\frac{\exp(-\alpha p_{nit} + \beta' x_{nit} + \eta_{nit})}{\sum_j \exp(-\alpha p_{njt} + \beta' x_{njt} + \eta_{njt})} \right) f(\theta) d(\theta) \tag{4}$$

As with the non-cost attributes we once again use a normal distribution to capture the heterogeneity associated with the cost coefficient, i.e., $\alpha \sim N(\mu, \sigma)$.

As noted by Bujosa et al. (2010), however, there may be a possible need for more than one distribution to represent random heterogeneity. They note that in the presence of different groups of individuals with different group specific tastes, the RPL model might be inadequate[2]. Whilst assuming within group homogeneity, as represented by finite distributions, might be too stringent. As a result we apply the mixtures of Normals approach to allow additional heterogeneity associated with each of two discrete points. This specification allows additional flexibility in the specification of the cost coefficient compared to the other alternatives explored in this paper. Other studies that have applied the mixtures of Normals approach include Wasi and Carson (2011), Fosgerau and Hess (2009) and Boeri (2011). Similarly, Bujosa et al. (2010) and Hensher and Greene (2013) extend the traditional latent class model with all fixed coefficients to a random parameters latent class model, which enables within class preference heterogeneity.

Following Fosgerau and Hess (2009) we combine a standard continuous mixture approach with a discrete mixture approach. Specifically, the mixing distribution is itself a discrete mixture of more than one independently distributed Normal distribution. In the context of cost the approach would allow for two groups of respondents based on their sensitivity to cost. One group may have a strong dislike for higher prices (a highly price sensitive group), and the other may have a low price sensitivity (and may be indifferent to the cost attribute), while there may be additional cost heterogeneity associated with each subgroup. If there is no additional heterogeneity associated with the cost coefficients within each subgroup then the distributions are reflected by the standard DM approach and the choice probability is represented by Equation 3.

For the mixture of distribution approach we combine Equation 3 and Equation 4 and the resulting choice probability becomes:

$$\text{Prob}(y_n) = \sum_{m=1}^{m} \pi_m \left[\int_{\theta_m} \prod_{t=1}^{T_n} \left(\frac{\exp(-\alpha_m p_{nit} + \beta' x_{nit} + \eta_{nit})}{\sum_j \exp(-\alpha_m p_{njt} + \beta' x_{njt} + \eta_{njt})} \right) f(\theta_m) d(\theta_m) \right] \quad (5)$$

In this model we specify two mean parameters μ_m to represent the heterogeneity surrounding the cost coefficient, and a correspondent set of standard deviations σ_m. For each pair of parameters (μ_m, σ_m), we then define a probability, π_m. The resulting distribution allows for m separate modes, where the different modes can differ in mass. As a result our cost attribute is represented by a combined RPL-DM approach, which has both discrete points and continuous distributions. Whilst our non-cost attributes have the same specification as the previous models and are represented by the standard RPL approach.

[2]We have defined RPL models here narrowly to represent models that include unimodial continuous distributions as represented by Equation 2 and Equation 4. As pointed out by a reviewer, however, our definition is restrictive and narrow given that RPL models in principle also includes discrete mixture models and is synonymous with Mixed Logit Models.

2.0.2 WTP Space Models

Following Train and Weeks (2005) we can divide the utility function as outlined in Equation 1 by a scale factor k that does not impact on behaviour but results in an error term that has the same variance for all decision-makers:

$$U_{nit} = -(\alpha/k)p_{nit} + (\beta/k)'x_{nit} + \eta_{nit} + \varepsilon_{nit}, \tag{6}$$

where ε_{nit} is an *i.i.d* type-one extreme value with constant variance. The utility functions are defined as $\lambda = (\alpha/k)$ and $c = (\beta/k)$ where utility can be written as

$$U_{nit} = -\lambda p_{nit} + c'x_{nit} + \eta_{nit} + \varepsilon_{nit}, \tag{7}$$

since WTP for an attribute is the ratio of the attribute's coefficient to the price coefficient: $w = c/\lambda$ As a result the WTP space utility specification can be written as:

$$U_{nit} = -\lambda p_{nit} + (\lambda w)'x_{nit} + \eta_{nit} + \varepsilon_{nit}, \tag{8}$$

The advantage of such a specification is that the distribution of WTP is estimated directly. It has been shown that in WTP space models the distribution of WTP is not as sensitive to extreme outlying values (e.g., Scarpa et al., 2008; Train and Weeks, 2005; Sonnier et al., 2007; Balcome et al., 2009) compared to preference space models. As noted by Train and Weeks (2005) under this parameterization, the variation in WTP, which is independent of scale, is distinguished from the variation in the price coefficient, which incorporates scale.

For this paper we run two WTP space models for comparative purposes. We include a specification where we assume that $-\lambda$ follows a unimodial Normal distribution. In this case the WTP space RPL model becomes:

$$\text{Prob}(y_n) = \int_\theta \prod_{t=1}^{T_n} \left(\frac{\exp(-\lambda p_{nit} + (\lambda w)'x_{nit} + \eta_{nit})}{\sum_j \exp(-\lambda p_{njt} + (\lambda w)'x_{njt} + \eta_{njt})} \right) f(\theta)d(\theta) \tag{9}$$

Under the WTP space specification we redefine θ to represent the combined vector of λ, w and η. A crucial point, that is particularly noteworthy in a paper with this focus, is that in WTP space models the cost coefficient is now confounded with the scale parameter. As a result, while we discuss the cost coefficient within the WTP space models, the coefficient is not directly comparable to the cost coefficient estimated in the preference space models.

Given that the central focus of this paper is the use of mixtures of distributions approach, we can amend the standard WTP space model specification as outlined by Equation 9 to accommodate a discrete and continuous representation of our cost coefficient, which is confounded with the scale parameter. As a result our model specification becomes:

$$\text{Prob}(y_n) = \sum_{m=1}^{m} \pi_m \left[\int_{\theta_m} \prod_{t=1}^{T_n} \left(\frac{\exp(-\lambda_m p_{nit} + (\lambda w)' x_{nit} + \eta_{nit})}{\sum_j \exp(-\lambda_m p_{njt} + (\lambda w)' x_{njt} + \eta_{njt})} \right) f(\theta_m) d(\theta_m) \right] \tag{10}$$

Similar to Equation 5 we estimate two mean parameters, a set of probabilities and two standard deviations for our cost coefficient, which is confounded with scale.

3 Background to the study and survey design

3.1 Policy context for the research

Ireland is a particularly unique case study to examine the recreational walking benefits of farmland. This is because the rights of access to the countryside belongs primarily to private landowners (who are mostly farmers). In many other developed countries public access provision for walking in the countryside is frequently enshrined in legislation or custom or both. Where neither legislation nor custom prevail, provision is often achieved through specifically designated areas (recreation areas and national parks) or by voluntary access arrangements. Neither legislation nor custom applies in the case of Ireland. While some rights of way do exist in Ireland, the network is quite fragmented and limited.

There are a small number of official and quasi-official schemes in Ireland for promoting outdoor walking opportunities. The principal ones are the Sli na Slainte Scheme and National Way-marked Ways. Currently there are over 160 Sli na Slainte walking routes. These are mainly over public roads in or close to villages/towns or cities. In addition, there are 31 National Way-Marked Ways covering a distance of approximately 3,421 kilometres (Buckley et al., 2008a). However, approximately half of these are on country roads and just over a quarter are on Coillte lands [3]. The remainder of the walkways traverse private property, national parks or other public lands.

Ireland also has an abundance of walks on commonage land. Although some of these are documented in guidebooks and appear on websites they are not covered by access agreements with landowners and no one is responsible for their maintenance. According to Buckley et al. (2009a) this represents an unsatisfactory situation and serves as no basis for permanently developing countryside walking opportunities.

Policy-makers in Ireland recognise that there is an under-supply of public ac-

[3]Coillte is Ireland's main semi-state operated forestry body

cess to the Irish countryside. To improve the provision of countryside walking opportunities a legislative framework 'Access to the Countryside Bill' was proposed in 2007. The Bill included a right of access to land in excess of 150 metres above sea level and to any open and uncultivated land, including bogs. This Bill met with strong resistance from the farm organisations who were opposed to any possible solution that might diminish their property rights (Buckley et al., 2008a).

In 2004, the responsible Ministry (Community, Rural and Gaeltacht Affairs) set up a Countryside Recreational Council 'Comhairle Na Tuaithe'. The role of this Council was to examine the issue of access to the Irish countryside. A walks scheme was agreed by stakeholders in Comhairle na Tuaithe in 2007 where landowners would be compensated for walkway development and ongoing maintenance. The scheme applies to over 40 trails which traverse both public and private land. At the end of 2010, there were over 1800 landowners participating in the scheme.

The first large-scale empirical study of farmers' preferences for providing access to their land for recreational walking was conducted by Buckley et al. (2009b). In their study they found that almost half of farmers surveyed indicated they would be willing to provide access to their land for walking. For the farmers who were unwilling to provide access, their main stated reasons for non-participation were; concern over interference with agricultural activities, insurance liabilities, privacy concerns as well as fear of walkers encountering dangerous livestock. The conditions under which these farmers stated they would be willing to provide access were: walkers must stick to a specific route (or walking trail), adherence by walkers to a countryside code of practice, no permanent right of way would be established, full insurance indemnification and provision of maintenance costs for the walking trails. In addition, farmers who had previous experience of walkers using their land were found to be more likely to facilitate access on their land to recreational walkers. This is an encouraging finding since most of the land in Ireland is owned privately by farmers, the study by Buckley et al. (2009b) suggests a willingness amongst farmers to increase recreational opportunities in the Irish countryside.

3.2 Survey design and data description

Given the policy focus surrounding access issues in Ireland, we developed a DCE study to elicit public preferences for the development of walking trails on farmland. The design of the DCE survey instrument involved several rounds of development and pre-testing. This process began a stakeholder meeting which included representatives from recreational and health bodies, tourist bodies, farming representatives and representatives from state and semi-state bodies. It should be noted that Colombo et al. (2009) observed that expert opinion can, in some cases, be used to represent citizens views for providing public rights of way in England. 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 in the field.

After the qualitative discussions, it was decided to use labelled alternatives to reflect 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.

In the final version of the questionnaire, five attributes were decided upon to describe the walking trails. 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 with 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 time interval levels to reflect the fact that not everyone walks at the same pace. 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 either paved and/or signposted. These three attributes represented the infrastructural features that were deemed important and realistic for farmland walking trails based on findings from the focus groups. 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. An example of a choice task used for the DCE is given in Figure 1.

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 between 2008 and

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

Figure 1: Example Choice Card

2009 using face-to face interviews. A quota controlled sampling procedure was followed to ensure that the survey was nationally representative of the population aged 18 years and above. The data used for model estimation included 3,372 observations from 281 rural individuals.

3.3 Model estimates

Table 1 reports the estimated output from six models. Models 1-4 are estimated in Preference Space (PS), and Models 5-6 are estimated in WTP space (WTPS). Model 1 (PS:cost fixed) is where the Cost coefficient is specified as fixed. Model 2 (PS:cost DM) assumes that the Cost coefficient can be adequately represented with two support points under the DM approach. Model 3 (PS:cost cont) is based on the premise that the Cost attribute has a single continuous mixing distribution. Model 4 (PS:cost DM+cont) is an extension of the second and third models, which specifies two discrete continuous distributions (i.e., a mixture of Normals) to describe the pattern of unobserved heterogeneity associated with the cost coefficient. Respectively, Models 5 (WTPS:cost cont) and 6 (WTPS:cost DM+cont) have the same specification for the cost coefficient as the third and fourth models but are estimated in WTP space. In all models the choice probabilities are approximated in estimation by simulating the log-likelihood with 400 Modified Latin Hypercube Sampling draws (Hess et al., 2006).

Table 1: Model results

		1. PS:cost fixed		2. PS:cost DM		3. PS:cost cont.		4. PS:cost DM+cont		5. WTPS:cost cont.		6. WTPS:cost DM+cont	
		est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.
Cost	μ_1	-0.046	-23.55	-0.018	-8.05	-0.127	-15.20	-0.069	-7.80	-0.113	-15.01	-0.015	-3.97
	σ_1					0.104	14.61	0.034	3.91	0.076	14.58	0.011	2.12
	π_1	1.000	fixed	0.621	17.96	1.000	fixed	0.461	9.86	1.000	fixed	0.705	16.27
	μ_2			-0.212	-14.97			-0.414	-9.65			-0.213	-11.00
	σ_2							0.165	8.84			0.107	10.56
	π_2			0.379	11.39			0.539	11.52			0.295	6.77
Length	μ	-1.216	-10.43	-1.338	-10.18	-1.255	-10.52	-1.505	-11.75				
	σ	1.493	12.08	1.814	14.00	1.630	13.41	1.598	12.66				
	μ_w									-12.643	-8.52	-10.671	-9.33
	σ_w									15.744	8.93	11.145	9.89
Car Park	μ	0.143	1.88	0.298	3.60	0.299	3.73	0.294	3.48				
	σ	0.699	6.99	0.686	5.88	0.671	6.29	0.747	6.12				
	μ_w									2.280	3.28	2.167	3.99
	σ_w									4.219	4.35	2.407	4.08
Fence	μ	0.209	2.43	0.208	2.14	0.249	2.64	0.207	2.01				
	σ	0.303	1.63	0.486	1.99	0.348	2.39	0.627	4.47				
	μ_w									1.767	2.106	0.949	1.39
	σ_w									2.902	1.465	3.123	2.94
Path	μ	0.474	6.12	0.487	5.77	0.517	6.53	0.499	5.88				
	σ	0.575	4.69	0.565	4.10	0.383	2.39	0.437	2.61				
	μ_w									3.44	4.417	2.386	4.06
	σ_w									4.372	3.530	3.355	3.36
Hill	μ	0.888	6.27	1.721	11.43	1.647	11.20	2.065	13.11				
	μ_w									9.326	7.092	7.27	7.62
Bog	μ	0.434	3.13	1.111	7.17	1.157	8.21	1.444	9.04				
	μ_w									8.211	6.89	6.570	7.31
Field	μ	0.647	5.72	1.491	9.12	1.417	9.12	1.824	11.00				
	μ_w									9.583	7.69	8.200	8.99
River	μ	1.323	9.73	2.322	14.40	2.183	14.84	2.694	16.10				
	μ_w									15.472	11.62	11.413	10.91
η (Hill/Bog)	σ_ϵ	0.881	7.34	0.934	7.90	0.605	5.28	0.804	6.19	0.698	5.31	0.836	5.94
η (Hill/Field)	σ_ϵ	0.987	7.92	1.004	8.84	1.036	8.96	0.867	6.18	1.101	8.76	1.056	8.01
η (Hill/River)	σ_ϵ	1.037	8.58	0.885	6.84	1.048	8.62	1.041	7.88	1.285	11.56	1.288	10.71
η (Bog/Field)	σ_ϵ	0.876	6.02	0.838	6.42	0.887	6.89	0.912	7.01	0.759	4.82	0.738	4
η (Bog/River)	σ_ϵ	0.775	6.21	1.001	8.56	0.733	4.61	0.905	7.42	0.707	4.59	1.107	7.53
η (Field/River)	σ_ϵ	0.682	4.09	0.841	6.24	0.863	8.19	0.814	6.66	0.864	6.94	0.876	6.99
$\mathcal{L}(\hat{\beta})$		-3,376.14		-3,058.17		-3,103.70		-3,011.99		-3,172.40		-3,124.89	
k		19		22		20		25		20		24	
Pseudo R^2		0.259		0.324		0.315		0.334		0.301		0.309	
BIC		6906.6220		6295.0637		6369.8712		6227.0675		6507.2672		6444.7543	
AIC		6790.2800		6160.3520		6247.4060		6073.9860		6384.8020		6297.7960	
3AIC		6809.2800		6182.3520		6267.4060		6098.9860		6404.8020		6321.7960	
crAIC		6795.0428		6167.6065		6252.9224		6084.4793		6390.3184		6307.1206	

μ and σ are used respectively to represent the mean and standard deviation of the random coefficients, a w subscript indicates the values for the WTP space models. π is used to denote the probabilities associated with the mass points for models that include discrete mixtures. $\mathcal{L}(\hat{\beta})$ denotes the log-likelihood value for each model. k is the number of parameters. Pseudo R^2 represents a model fit criterion. The BIC, AIC 3AIC and crAIC represent information criteria developed by Hurvich and Tsai (1989) that penalise for the number of parameters estimated (for a more in-depth discussion of the criteria, see.g., Hynes et al., 2008).

Turning our attention first to the non-cost attributes in model 1 (PS:cost fixed), the mean coefficient for Length, which is a dummy variable for longer walks[4], is negative, suggesting the general preference is for walks of a shorter duration. Nevertheless, the retrieved coefficient of variation for the Length attribute is relatively large, implying that a share of respondents do prefer taking walks over two hours duration. This is not surprising as individuals are likely to differ in their fitness levels and general preferences for engaging in farmland walks. The mean coefficient for the Car Park attribute is positive, albeit only significant at the ten percent level. However, the standard deviation is significant, indicating some respondents do have a preference for car park facilities while another proportion do not. This potentially suggests that a sizeable proportion of respondents may dislike having a gravel car park near a walking trail because they may associate it with issues of crowding at the walking sites or they may prefer more naturally developed walking trails. A similar result is obtained for the Fence attribute. This verifies the feedback from the focus group discussions, where some participants considered a fence would provide safety from livestock, whilst others felt a fence would restrict their walking experience. As indicated by the positive mean coefficient for Path, the majority of respondents prefer walking trails that are paved. Relative to the stay at home option, all the alternative specific constants are positive and significant—implying that respondents' have a general preference for participating in a farmland walk versus staying at home. Based on the estimated coefficients, the most preferred walk type is River walks and the least is Bog walks, with Hill and Field walks ranking in-between. The error components between the walk alternatives are all significant suggesting that correlation and substitution exists between the walks. The fixed cost coefficient is negative and significant as expected.

Model 2 (PS:cost DM) specifies the cost coefficient to take two discrete values. This leads to a large improvement in model fit (an increase of 318 log-likelihood units at the expense of 3 additional parameters), which provides strong evidence against the use of a fixed cost coefficient and its implied equal marginal sensitivity to cost across individuals. The model specification partitions respondents into two distinct groups, based on the cost coefficient. The first group, representing approximately 62 per cent of the sample are quite insensitive to cost (as the discrete distribution lies in the negative domain but is close to zero), with the second group estimated with a high sensitivity to cost (highlighted by its further distance from zero). For the first group this low sensitivity to cost might reflect the fact that some respondents are not strongly opposed to engaging in walking trails that have a higher travel cost. The low sensitivity group may include respondents who have not attended to the cost attribute (which in this study represents distance), which explains why their cost coefficient is estimated very close to zero. Within the DCE literature, the issue of attribute non-attendance

[4]The attribute levels representing walks of between 2-3 hours and 3-4 hours in Length were combined as their estimated coefficients were not statistically different

has been given considerable attention (e.g., Hensher and Rose, 2009; Campbell et al., 2011; Scarpa et al., 2010, 2009), with some studies highlighting how cost can often be the most ignored attribute (Scarpa et al., 2009). While we do not explicitly accommodate non-attendance in estimation, given the growing literature, we suspect that our low sensitivity includes respondents who have not attended to cost as well as respondents' who have attended to cost (or distance) but were not highly sensitive to it. Additionally, recent studies have shown that scale differences may occur within and between discrete groups (Magidson and Vermunt, 2008; Boeri et al., 2011; Campbell et al., 2011). For instance, as noted by Campbell et al. (2011), each discrete point may be comprised of a subset of respondents, while having the same preferences, differ in their level of uncertainty and hence variance leading to different scale factors. Furthermore, Boeri et al. (2011) has shown how scale differences can emerge between discrete classes within the latent class modelling framework. The signs and significance of the non-attribute coefficients are similar to the first model, except the mean coefficient representing the car park attribute is significant.

In the third model we specify the cost coefficient to follow a single continuous distribution. As can be seen from Table 1 this is estimated with fewer parameters compared to when we specify cost with two discrete points. However the BIC and AIC criteria suggest that the model represents a worse fit compared to the previous specification. Additionally, the coefficient of variation for the Cost coefficient is relatively high under this specification suggesting a share of the distribution is within the positive domain. This could reflect a share of respondents who are either relatively insensitive to cost or may not have attended to the distance attribute within the CE. However it could also, in part, be an artefact of using a single continuous Normal distribution to represent the heterogeneity of the population with respect to cost.

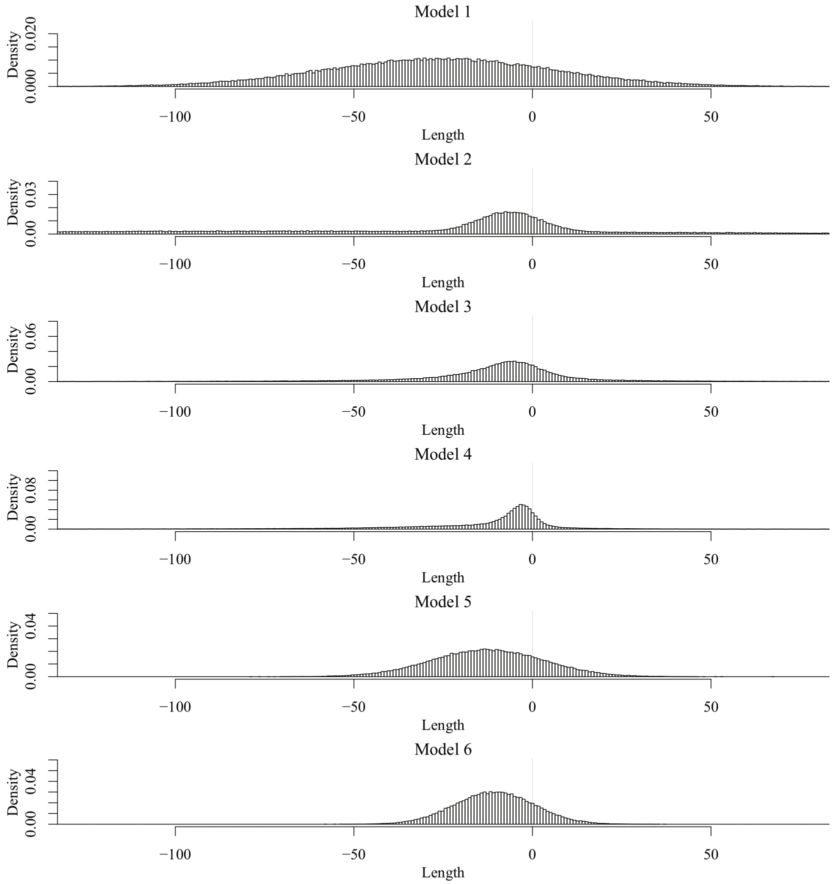
In Model 4 (PS:cost DM+cont) the Cost attribute is specified with a mixture of distributions. We assume two discrete mean coefficient values each with an associated probability representing the discrete approach taken for Model 2 (PS:cost DM). The approach also allows additional heterogeneity within the two subgroups specified. The approach relaxes the assumption that every respondent lies on the same distribution with respect to Cost. This model assumes a further improvement in model fit. As reflected by the Pseudo R^2, the BIC and AIC criteria this improvement is found even after penalising for the additional parameters. There is a lower share of respondents ($\pi = 0.461$) estimated to belong to the low cost sensitivity group compared to the share predicted by the second model ($\pi = 0.531$). Unlike Model 2 (PS:cost DM), which assumes homogeneity within the subgroups, we find strong evidence of heterogeneity with respect to cost, as both the standard deviations' are highly significant in this model. The remaining parameters are estimated with similar significance and magnitudes as in the previous models. However, we note that the coefficients of variations tend to be of a smaller magnitude, suggesting that for this dataset at least, allowing for additional heterogeneity with respect to cost leads to lower variation with respect to the non-cost attributes. This result implies that some of the variation with respect to the cost attribute was potentially being captured by the non-cost attributes, which may impact on subsequent policy decisions.

Our final two models presented in Table 1 are estimated in WTP space. To reduce the number of models, we only present the results from two WTP space specifications. Model 5 (WTPS:cost cont) assumes a single continuous distribution for the Cost coefficient. The mean of this distribution is found to be of a similar magnitude as Model 6 (PS:cost DM+cont) , but as signified by the relative standard deviation, the degree of heterogeneity is somewhat smaller. A useful feature of WTP space models is the derivation of WTP directly. As can be seen, the mean WTP estimates for all parameters are significantly different from zero. The non-Cost attributes also have significant standard deviations. In terms of welfare associated with the non-cost attribute, most disutility is associated with longer length walks. For the remaining attributes, the mean WTP for path and signage is largest, followed by car park. For the fence attribute there is substantial welfare heterogeneity. Quite a large proportion of individuals are estimated to have both positive and negative WTP estimates for the fence attribute.

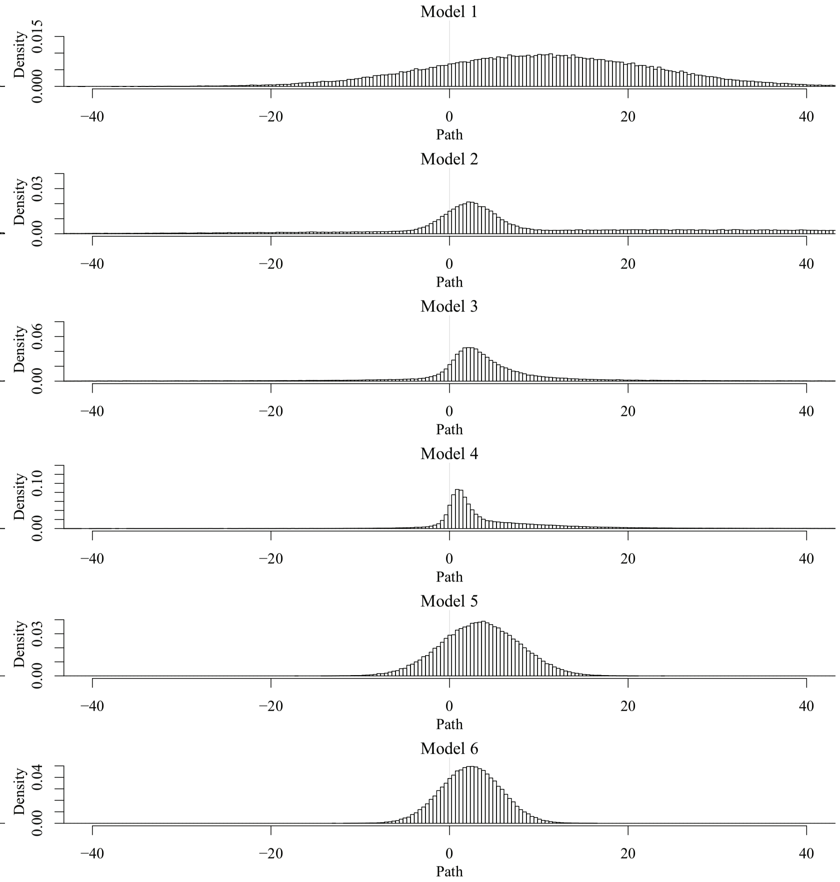
In the final model we specify a mixture of distributions to represent the heterogeneity associated with the Cost attribute. The mean estimates and standard deviations are all found to be significant. The results for the cost coefficient are somewhat different to those obtained under model 4 (PS:cost DM+cont). Under Model 6 (WTPS:cost DM+cont), the majority of respondents ($\pi = 0.705$) are associated with a relatively low valued cost coefficient (which is similar to the result attained in Model 2). The mean WTP estimates retrieved from this model are similar to those attained under the previous WTP specification (albeit with quite a lower estimated mean WTP for the length attribute) but the standard deviations are relatively smaller. The WTP space models achieve better fits over the first model but they do not perform better than the remaining preference space models. This is similar to the results presented by (e.g., Train and Weeks, 2005).

3.4 Implications for welfare estimation

Figure 2 illustrates the impact of the different distributional assumptions for the cost coefficient on the retrieved unconditional WTP estimates for two of the non-cost attributes. The distributions are estimated through simulation (see e.g. Hensher and Greene 2003, for an in-depth discussion) where 10,000 draws are taken from the distribution of the non-cost and cost attributes, and the ratio of the non-cost to cost attribute is calculated for each draw. The ratios are draws from the distribution of WTP (Daly et al., Forthcoming). Under the first model (PS:cost fixed), since Cost is the denominator and is fixed, the distribution of WTP takes on the same distribution as the non-Cost coefficient, thus facilitating straight-



(a) (Unconditional) WTP distributions for Length



(b) (Unconditional) WTP distributions for Path and Signage

Figure 2: Comparison of (unconditional) WTP distributions

forward WTP estimation. However, as shown, in the case of all attributes, this model produces distributions that are relatively more dispersed than those estimated when heterogeneity in the cost coefficient is accommodated. There is a general reduction in the degree of WTP dispersion as one moves to the fourth model which uses a mixture of distributions approach.

We present median WTP in Table 2 as Balcome et al. (2009) note that median values are more stable than mean estimates for RPL models estimated in preference space. Across all models, the median WTP estimate to avoid a longer length walk, is relatively large compared to the utility associated with the other attributes. Therefore in general, individuals have a strong preference for farmland walks that are relatively shorter in duration. This likely reflects the walking habits of the Irish population, where not that many individuals engage in walks that are over two hours duration. For the remaining attributes, the WTP for path and signage is largest, followed by car park. The relatively lower WTP estimate for the fence attribute likely reflects the substantial heterogeneity associated with this attribute under the models. In general the models suggested that a proportion of individuals had both positive WTP for a fence and a proportion who are WTP to avoid a farmland trail that is fenced-off from livestock. Although not unexpected, this has some implications in terms of the implementation of farmland walking trails as it suggests, a mixture of trails is necessary that differ in terms of their features.

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

Model	Length Long	Car Park	Fence	Path
1.PS: Cost fixed	-29.31	3.65	5.18	11.61
2.PS:cost DM	-15.29	3.4	2.25	5.23
3.PS:cost cont	-6.91	1.59	1.37	2.92
4.PS: cost DM+cont	-5.87	1.19	0.82	1.92
5.WTPS:cost cont	-12.77	2.33	1.78	3.51
6.WTPS: cost DM+cont	-10.82	2.21	0.91	2.34

As evident from Table 2 the distributional assumptions associated with the cost attribute has an impact on the retrieved WTP estimates. Taking the longer length attribute as an example, there is a huge reduction in the median WTP estimate between the first and the fourth model specification. It must be noted that while lower welfare estimates are retrieved from Model 4(PS: cost DM+cont), they are similar to the estimates from the other models with random cost coefficients. In particular, the estimates do not differ substantially between the third and fourth model specification in preference space. For the WTP space models slightly lower welfare estimates are retrieved from the Model 6 (WTPS: cost DM+cont) compared to Model 5 (WTPS:cost cont). Overall, our best model fit was associated with the preference space model using the mixtures distribution for cost.

Generally the lower estimates retrieved from this model, compared to the other specifications that included discrete mixtures, most likely reflects the lower estimated share of respondents associated with a mass point closer to zero in this model. We also find that using a fixed cost coefficient is both associated with a poorer model fit and larger retrieved welfare estimates. Hence, we find little support for this approach either empirically, based on the model fit, or from a policy perspective, based on its associated welfare estimates. However, whilst the retrieved median estimates are larger under this model, we do not know what the true underlying WTP values are to speculate on which model specification provides the closest estimates to the true values. We must acknowledge, also that our WTP estimates may reflect the higher bound in term of welfare estimates because it is based on the assumption that the person answering the survey would bear all the out of pocket travel expenses. In Ireland, previous studies have found that between 38 and 50 percent of people indicate that they walk alone for long and short walks respectively. In the case of short and long walks (up to 4 hours) approximately 38 and 45 percent of respondents indicate that the walk with one other companion only. Of the people who walk with one other companion approximately 60 percent walk with another family member or partner. As a result we would expect that in the majority of cases, costs are most likely borne either directly by the person answering the survey or within their household. Nevertheless, it could be likely that some respondents answering the choice experiments would assume that they would not have to bear the full costs themselves of travelling to the walks and as a result our estimates most likely reflect the upper bound in terms of individual WTP. As noted by a reviewer the low cost sensitivity groups that we observed may reflect individuals who assumed that they would not have to bear the full costs of travelling to the sites.

4 Conclusion

Since the value of farmland as a recreational resource is potentially high, a careful assessment of the benefits from this resource is essential when deciding on the alternative uses of farmland. Determining the preferences of potential recreational users' is useful from a policy perspective as it allows managers, landowners and other stakeholders with the necessary information to provide suitable amenities at recreational sites. To this end, this paper explored preferences of Irish rural residents for the provision of farmland walking trails in the Irish countryside. In Ireland, property rights are such that recreational users do not currently have the same access to the countryside as other European countries. As a result, a stated preference study using the CE methodology was employed to elicit these preferences.

A further objective of this paper was to compare alternative methods to accommodate heterogeneity associated with the cost coefficient in a RPL model of recreational site-choice. We compared a number of models assuming either a discrete, continuous or mixture of discrete and continuous distributions, to represent cost heterogeneity. Our reference model assumed a fixed cost coefficient, and the remaining models allowed for different random specifications for cost. We also compared the distributional implications for the cost coefficient in preference and WTP Space. We found that the preference space model which enabled additional cost heterogeneity using a combination of discrete and continuous mixing distributions provided the best fit for the data. Beyond this, we also found that this model specification was associated with the lowest WTP distributions for the non-cost attributes explored in this study. However, in general, the policy implications arising from the models, where the cost coefficient was specified as random, did not differ substantially from each other. In general we found little support empirically for fixing the cost coefficient in RPL models, which echoes findings by Balcome et al. (2009).

In choosing which random distribution to use for the cost coefficient a number of points are noteworthy. First, the DM approach (without including the continuous distribution) may be useful in situations where the analyst wishes to constrain all cost heterogeneity to be in the negative preference domain. An advantage of this approach is that the analyst is not required to specify a particular distribution for the random heterogeneity and it makes welfare estimation more straightforward. On the other hand the mixtures of distribution approach may be useful when the analyst does not have strong *a priori* expectations, for either cost or non-cost attributes, regarding the shape of the distributions. In particular the additional parameters associated with the mixtures approach means that it is more capable of representing a range of potential distributions. While our focus on the cost coefficient may be somewhat arbitrary it mirrors a growing interest within the literature in using multi-modality distributions to represent unobserved heterogeneity (e.g., Fosgerau and Hess, 2009; Fosgerau and Bierlaire, 2007; Scarpa et al., 2008; Hensher and Greene, 2013). Campbell et al (2010) show how the mixtures of distributions approach can be extended to a number of attribute coefficients in their preference space models. However, we must acknowledge some limitations of the approach. In the preference space models, while we noticed a lower mass at the extremes of the WTP distribution we did not find that the mixtures of distributions approach overcomes the problem of obtaining extreme WTP estimates at the tails of the distribution. Additionally, where the distribution traverses zero, as in the case of the normal distribution for cost, the WTP distribution may not have well-defined moments in preference space (Daly et al., Forthcoming). We did not observe these problems with the mixtures approach in WTP space. An avenue for further research is to examine the applicability of the approach to other distributions. In the case of the cost coefficient, for instance, a mixture of distributions that ensure that the distribution is bounded below zero may be advantageous to ensure the distribution of WTP has well-defined moments in preference space. In the case of the WTP space model specification bounding the distribution for cost is likely to be advantageous because it ensures that the scale parameter is bounded below zero to ensure finite variance. We explored the possibility of using the mixtures approach with the Johnson SB distribution, which can be bounded. However, we found a mixtures of distributions did not work well for the Johnson SB distribution, which is most likely due to the number of parameters required to estimate this distribution. Furthermore, while we do not include covariates without our model specifications, we note that their inclusion could enhance the generalizability of the approach we have used.

Notwithstanding the fact that we found significant heterogeneity associated with each attribute, a few general policy observations should be noted. First, countryside residents showed a much stronger preference for walking trails that are shorter in length. This has implications for the development of these trails because it implies that only smaller tracks of farmland may be needed to develop the trails and hence, less cost should be associated with their development. In terms of the other attributes, generally, car-parking facilities and path and signage facilities were favoured by the majority of respondents. Approximately half of respondents favoured trails that were fenced off from livestock. This suggests that a mixture of trail types may be warranted, with different infrastructural features. In general, Irish rural residents showed the highest preference for river farmland walking trails. Given that rivers are spread throughout the Irish countryside this result suggested that substantial supply side potential may exist to develop these trails, if farmers are willing to participate in such farmland walkway schemes. While the other walk types, namely hill, field and bog walks were not as strongly preferred as river walks, Irish countryside residents did also show a positive preference for these walks. These results confirm that significant demand exists for more extensive development of the Irish countryside for recreational pursuits. Providing access to the countryside for recreation would bring Ireland in line with the majority of other European countries.

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