Combining discrete and continuous mixing approaches to accommodate heterogeneity in price sensitivities in environmental choice analysis*

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Abstract

Data from a discrete choice experiment aimed at eliciting the demand for recreational walking trails on farmland in the Republic of Ireland is used to explore the consequences of misspecifying the cost coefficient. To enable straightforward calculation of WTP from the distributions of the non-price coefficients, the price coefficient is typically held constant in mixed logit models. This implies that all respondents are equally price sensitive. In this paper we test the validity of this assumption. Our approach is based on a comparison and combination of discrete and continuous mixing approaches (i.e., a mixture of distributions) to uncover the unobserved heterogeneity in price sensitivities. Results from the analysis highlight that model fit and willingness to pay are sensitive to the distributional assumptions used to represent the price coefficient.

Keywords: Discrete choice experiments; discrete mixtures; continuous mixtures; mixtures of distributions; price sensitivities; farmland recreation; willing to pay space

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1 Introduction

Discrete choice experiments 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. This approach to preference estimation and value derivation techniques is appealing because it is consistent with the Lancasterian microeconomic approach and because it is behaviourally grounded on random utility theory. Thanks to recent developments in simulation methods in estimation of open form probability integrals, the estimation of discrete choice models with random coefficients has become standard practice. However, there is still ongoing debate regarding the appropriate distributional form to represent the random taste variation. This is especially important when the random parameters are used to derive estimates of marginal rates of substitution, such as WTP.

Specifying the cost attribute as random runs the risk of retrieving extreme (negative and positive) estimates for WTP. For this reason, in the majority of studies employing random parameters models, the cost coefficient is held constant. While this enables more straightforward calculation of WTP from the distributions of the non-price coefficients, it may be erroneous to assume that all respondents are equally price sensitive. For instance, as it is conceivable that respondents who are highly sensitive to price may follow a somewhat different distribution than those who are lowly sensitive. This raises the important question about how to appropriately accommodate heterogeneous price sensitivities.

A possible solution would be to enable the cost coefficient to have a small number of possible values, achievable using the discrete mixture approach described in Hess et al. (2007). While this approach should lead to a better representation of the heterogeneity in price sensitivity, the complete range in respondent's sensitivities to price may not be adequately explained with a relatively small number of values, suggesting the need for continuous distributions. However, as shown in (Campbell et al., 2010) and (Campbell and Hess, 2009) a single continuous distribution for random parameters may be inappropriate due to the fact that all respondents may not be located on the same distribution.

To illustrate this, consider a scenario in which there is a population in which half respondents have a cost coefficient distributed $\mathcal{N}(-0.8, 0.15)$ and that the remaining respondents have a cost coefficient distributed $\mathcal{N}(-0.2, 0.05)$. This leads to a distribution with two separate modes, as shown in Figure 1. However, fitting a single Normal distribution to this population implies $\mathcal{N}(-0.5, 0.32)$, which exaggerates the density of respondents in the intervals between the two modes, as shown in Figure 1. Moreover, the tails are much more pronounced, with the implication that a substantially large amount of the distribution is found to have the a counterintuitive sign. In this regard the mixtures of distributions, as discussed in (Coppejans, 2001; Geweke and Keane, 2001; Fosgerau and Hess, 2009), may

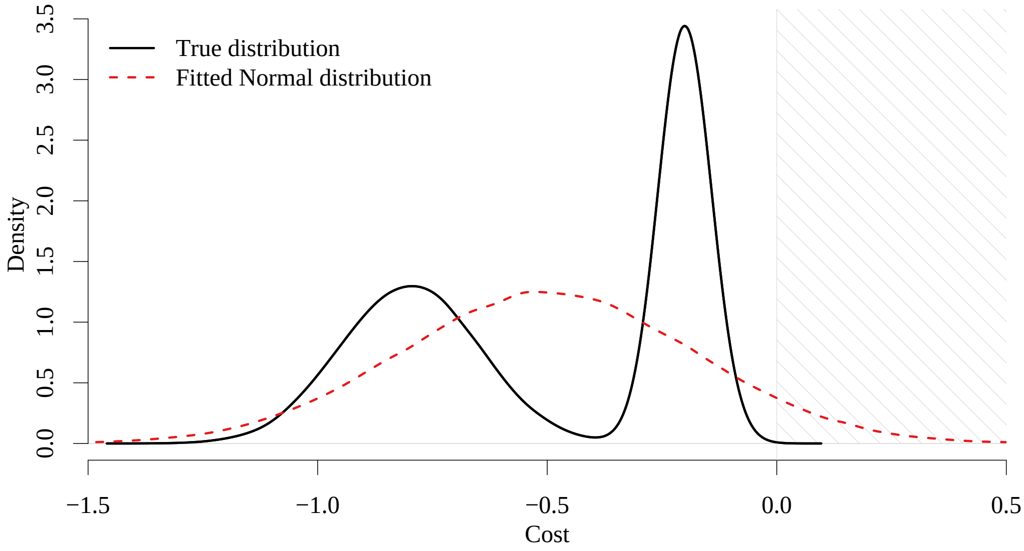


Figure 1: Example distribution affected by extreme sensitivities

provide some remedies. The advantage of such models are that they can facilitate the possibility of more than one distribution for the cost attribute and that they should help describe sensitivities to price more accurately.

Using data from a discrete choice experiment, this paper seeks to investigate the consequences of misspecifying the mixing distributions for the cost coefficient. The empirical dataset focuses on eliciting the demand for recreational walking trails on farmland in the Republic of Ireland. We start with the relatively common practice of fixing the cost coefficient and compare this with three alternative ways of representing the unobserved heterogeneity in price sensitivities across respondents in preference space and two specifications in WTP space. Our first modelling approach, assumes a discrete mixture representation for the cost coefficient. In our second modelling approach the cost coefficient is specified as having a continuous mixing distribution. Our third modelling approach attempts to accommodate the potential limitations of the discrete and continuous modelling specifications, whilst exploiting their respective strengths. To do this we estimate a model which combines discrete and continuous mixing approaches, whereby we have a mixture of distributions. We further estimate the previous two model specifications, but in WTP space.

Results from the analysis provide strong evidence that the manner in which random taste heterogeneity in price sensitivities is accommodated can have huge impact on model fit and performance. We provide supporting evidence for the use of WTP space models. Importantly, we further show that the magnitudes and robustness of the estimated WTP distributions are sensitive to the assumptions used to represent the price coefficient.

The remainder of the paper is structured as follows: Section 2 describes our econometric approach; Section 3 outlines our empirical case-study; Section 4 presents the results from the analysis; and, Section 5 concludes.

2 Methodology

In this paper we explore the implications of different distributional assumptions for dealing with heterogeneous price sensitivities. Starting with the conventional specification of utility, where respondents are indexed by n, chosen alternatives by i, the cost attribute by p and the vector of non-cost attributes by x, we have:

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

where α and β are the coefficients for the cost attribute and the vector of non-cost attributes respectively to be estimated and ε is an *iid* Gumbel distributed error term. If the value of α and β were known with certainty for each respondent, then the probability of respondent n's sequence of choices would be given by:

$$\text{Prob}\left(y_n|\alpha_n, p_n, \beta_n, x_n\right) = \prod_{t=1}^{T_n} \frac{\exp\left(-\alpha_n p_{nit} + \beta_n' x_{nit}\right)}{\sum_{j=1}^{J} \exp\left(-\alpha_n p_{njt} + \beta_n' x_{njt}\right)}, \tag{2}$$

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

It is clearly not possible to know the values of α_n and β_n with certainty. For this reason, there has been a growth in models which attempt to uncover and explain the heterogeneity across respondents. Indeed, in the environmental economics literature it is increasingly now common practice to use models, such as mixed logit specifications, to handle preference heterogeneity (e.g. Balcombe et al., 2009; Train, 1998; Hynes et al., 2008; Campbell, 2007), by treating the coefficients as random. Moreover, McFadden and Train (2000) have shown that these mixed logit models provide a flexible and computationally practical econometric method, which with adequate data quality, may in principle be used to approximate any discrete choice model derived from random utility maximization.

With θ representing the combined vector of α and β, the unconditional choice probability is obtained by integrating the logit probability, which is denoted by $L\left(y_n|\theta_n, p_n, x_n\right)$, over all possible values of θ_n:

$$\text{Prob}\left(y_n|\theta_n, p_n, x_n\right) = \int_{\theta_n} L\left(y_n|\theta_n, p_n, x_n\right) f\left(\theta_n\right) d\theta_n. \tag{3}$$

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, the most popular being Normal. For this reason, we specify the heterogeneity for all of the non-cost attributes as having a Normal distribution, $\beta \sim N(\mu, \sigma)$. For the cost parameter, however, it is well known that a Normal mixing distribution can imply behaviourally inconsistent values—due to the range of taste values over which the distribution spans (Hess and Axhausen, 2005). To eliminate this potential problem, the cost coefficient is typically held constant. But, this may be an erroneous assumption, as it implies homogeneous sensitivities to price.

In this regard, a discrete mixing distribution for the cost attribute may be advantageous. In a discrete mixture context, the number of possible values for a coefficient is finite (e.g., see Hess et al., 2007, for a review of discrete mixture models). In estimation this can be achieved by assigning α with m mass points, α_m, each of them associated with a probability π_m, with the following conditions:

$$\begin{aligned} 0 \leq \pi_m \leq 1, \text{ and} \\ \sum_{m=1}^{M} \pi_m = 1. \end{aligned} \tag{4}$$

Notwithstanding the fact that this should lead to a better representation of the heterogeneity in price sensitivities compared to a situation in which the cost coefficient is fixed, it may still not adequately capture the complete range of respondent's sensitivities to price. This leads us to the case of an infinite representation of sensitivities. In this paper we use the popular Normal distributional to capture the heterogeneity, i.e., $\alpha \sim N(\mu, \sigma)$.

However, as demonstrated in Figure 1 and shown in Campbell et al. (2010) and Campbell and Hess (2009) there may be a possible need for more than one distribution to represent cost (i.e., a mixture of distributions). 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 distributions. We specify a set of mean parameters μ_m 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 with the same conditions outlined in Equation 4. The resulting distribution allows for m separate modes, where the different modes can differ in mass (see Fosgerau and Hess, 2009, for further details).

Given the growing interest in WTP space models (e.g., Scarpa et al., 2008; Train and Weeks, 2005) it is also worth exploring whether there is any benefit for using mixtures of distributions to represent the price sensitivities in WTP space models. In this case, instead of the standard preference space specification described in Equation 1, the utility function is represented as follows:

$$U_{ni} = -\alpha p_{ni} + (\alpha w)' x_{ni} + \varepsilon_{ni}, \tag{5}$$

where $w = \beta/\alpha$. The advantage of such a specification is that the distribution of WTP is estimated directly.

3 Empirical case-study

This research sought to provide an insight into public preferences for the creation of farmland walking trails in the Republic of Ireland. At present, recreational opportunities for walking in the Irish Countryside are quite limited. For instance, there are few designated public rights of way or areas designed specifically for providing recreational enjoyment. In addition, the majority of land in the Irish countryside is privately owned by farmers. Unlike many other European Countries, recreational users do not have rights of access to farmland. As a result, residents in rural areas mainly use public roads for recreational walking, which Buckley et al. (2009b) suggest the Irish public may consider to be a "sub-optimal" experience.

This present study aims to assess the public demand for farmland walking trails in Ireland and stems from the research by (Buckley et al., 2009a), which reveals that many Irish farmers would be willing to provide the public access to their land for walking. Given the multi-attribute nature of countryside walking trails, we use the discrete choice experiment methodology. As part of this exercise, data was gathered from a stratified random sample of the Irish rural adult population, representative on gender, age, socio-economic status and geographical location.

The discrete choice experiment exercise reported here involved several rounds of design and testing. This process began with the gathering of opinions from stakeholders. To further define the attributes and alternatives, a series of focus group discussions with members of the public were held. Following the focus group discussions, the questionnaire was piloted, with the aim of checking the wording of the questionnaire and the respondent's acceptance of the choice scenarios. In the final version of the questionnaire, five attributes were decided upon to describe the walking trails. The first of these was 'Length', indicating whether or not the walk would be longer than 2 hours. The attribute 'Car Park' was used to denote if the walking trail had car-parking facilities. A 'Fence' attribute was used to indicate if the trail was fenced-off from livestock. The 'Path' was used to distinguish if the trail was paved and signposted. A further attribute was included, which represented the distance of the walk from the respondent's home. This attribute was later converted to a 'Cost' per trip.

In this study, a Bayesian efficient design, based on the minimisation of the D_b-error criterion, was used to generate the choice scenarios (for a general overview of efficient experimental design literature, see e.g., Scarpa and Rose, 2008, and reference cited therein). Our design comprised of a panel of twelve choice tasks. For each task, respondents were asked to choose between the experimentally designed alternatives and a stay at home option. The alternatives reflected the four main types of farmland walks in Ireland, namely 'Hill', 'Field', 'Bog' and 'River' walks. 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. Overall, this paper uses the responses from 281 respondents, resulting in 3,372 observations for model estimation.

4 Results

4.1 Model estimates

Table 1 reports the estimated output from six models. Model 1 is based on the common approach whereby the Cost parameter is specified as fixed (i.e., $M = 1$). Model 2 assumes that the Cost parameter can be adequately represented with two support points (i.e., $M = 2$), whereas Model 3 is based on the premise that the Cost attribute has a continuous mixing distribution. Model 4 is an extension of Models 2 and 3, which specifies two discrete continuous distributions (i.e., a mixture of Normals) to describe the pattern of unobserved heterogeneity in price sensitivities. Respectively, Models 5 and 6 use the same specification for the Cost attribute as Models 3 and 4, but using a WTP space specification. In all models the choice probabilities are approximated in estimation by simulating the log-likelihood with 250 MLHS draws (Hess et al., 2006). Normal distributions are used represent the unobserved heterogeneity of the non-cost attributes. While we acknowledge the choice of Normal distributions (and mixtures of Normal distributions) for the Cost coefficient does not guarantee a strictly non-positive distribution, our choice is based on the fact that Normals remain the most popular distribution amongst discrete choice analysts. We further note the number of discrete points and number of discrete mixtures could be further extended, our aim here is to demonstrate the merits of the approach.

As expected, Model 1 produces a negative cost coefficient. The mean coefficient for Length, which is a dummy variable for longer walks (i.e., greater than 2 hours in length), is also 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 a share of respondents who prefer taking walks longer than 2 hours. The mean coefficient for the Car Park attribute is positive, albeit not significant. Nevertheless, the standard devi-

Table 1: Model results

		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
		est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.
Cost	μ_1	-0.041	-23.47	-0.017	-7.85	-0.142	-13.79	-0.048	-7.46	-0.097	-14.00	-0.013	-2.62
	σ_1					0.121	12.64	0.036	7.20	0.068	10.88	-0.016	3.92
	π_1	1.000	fixed	0.586	15.97	1.000	fixed	0.435	8.57	1.000	fixed	0.672	13.91
	μ_2			-0.196	-13.43			-0.387	-9.49			-0.166	-10.45
	σ_2							0.185	9.48			-0.051	4.76
	π_2			0.414	11.28			0.565	11.12			0.328	6.79
Length	μ	-1.106	-9.42	-1.186	-9.27	-1.171	-9.58	-1.288	-10.31				
	σ	1.610	14.19	1.770	14.18	1.661	14.76	1.647	13.42				
	μ_w									-13.308	-7.71	-9.625	-6.05
	σ_w									19.076	10.71	16.172	9.57
Car Park	μ	0.100	1.30	0.271	3.40	0.286	3.8	0.259	3.47				
	σ	0.847	10.33	0.792	8.35	0.739	7.82	0.672	7.10				
	μ_w									2.342	2.69	2.416	3.26
	σ_w									7.864	7.09	-5.944	7.08
Fence	μ	0.109	1.29	0.129	1.43	0.125	1.42	0.127	1.42				
	σ	0.624	5.84	0.622	5.03	0.531	4.31	0.582	4.40				
	μ_w									0.755	0.78	0.689	0.83
	σ_w									5.503	4.15	-5.313	4.71
Path	μ	0.349	4.50	0.350	4.37	0.367	4.93	0.402	5.40				
	σ	0.764	8.07	0.738	6.75	0.584	4.40	0.541	4.34				
	μ_w									3.237	3.47	2.703	3.52
	σ_w									7.312	5.49	6.18	6.00
Hill	μ	0.880	10.42	1.520	15.43	1.690	16.06	1.919	17.90				
	μ_w									9.820	9.41	8.180	9.25
Bog	μ	0.353	3.91	0.965	9.44	1.127	10.41	1.340	12.10				
	μ_w									7.415	7.21	6.438	7.62
Field	μ	0.539	5.72	1.260	11.68	1.417	12.49	1.646	14.25				
	μ_w									9.413	8.85	8.515	9.58
River	μ	1.189	13.45	1.913	18.45	2.084	18.85	2.293	20.40				
	μ_w									15.470	13.34	13.359	13.42
$\mathcal{L}(\hat{\beta})$		-3,586.325		-3,247.868		-3,242.840		-3,170.499		-3,422.875		-3,400.449	
k		13		16		14		18		14		18	
$\bar{\rho}^2$		0.211		0.284		0.286		0.301		0.246		0.250	

ation is significant, indicating that a share of the sample who have a preference car park facilities and a share who do not. 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, respondents prefer walking trails that are paved. The standard deviation for this attribute is also significant. Relative to the stay at home option, all the alternative specific constants are positive and significant—implying that respondent's general preference is for farmland trails. The largest estimated alternative specific constant is associated with River walks and the least is Bog walks, with Hill and Field walks ranking in-between.

In Model 2, we specify the cost coefficient with two finite values. As can be seen, this leads to a large improvement in model fit (an increase of 338 log-likelihood units at the expense of 3 additional parameters), which provides strong evidence against assumption of homogeneous price sensitivities. The findings reveal that respondents can be partitioned into two distinct groups, based on their sensitivities to price. The first group of respondents ($\pi = 0.586$) are quite insensitive to price, with the remaining group estimated with a high sensitivity to price. The conclusions for remaining parameters in Model 2 are similar as those in Model 1 except that the mean coefficient for the Car Park attribute is significant (and remains so for Models 2–6).

In Model 3 we assume the price sensitivity heterogeneity follows a single continuous Normal distribution. As may be seen this leads to an improvement in model fit (and is estimated with fewer parameters). However, this improvement is only slight. We note that, the coefficient of variation for the Cost attribute is relatively high. In fact, using the estimated values of μ and σ, an approximated 12 percent of the distribution is within the positive domain. This is largely a consequence of using a Normal distribution. Therefore, despite the fact that a better model fit is obtained under Model 3 compared to Model 2, it allocates a large proportion of the distribution with the 'wrong' sign. The remaining parameters are estimated with similar significance and magnitudes as in the previous models.

Model 4 specifies the Cost attribute with a mixture of Normals. We assume two discrete mean coefficient values each with an associated probability representing the discrete approach taken for Model 2. The advantage of such an approach is that it does not assume that every respondent is on the same distribution with respect to Cost. Under this modelling approach, we obtain a further improvement in model fit. As reflected by the $\bar{\rho}^2$ this improvement is found even after penalising for the additional parameters. Again, we find the presence of a group of respondents ($\pi = 0.435$) who are not highly sensitive to price and a group who are highly price sensitive. Unlike Model 2, which assumes homogeneity within the groups, as both the standard deviations' are highly significant in this model we find strong evidence of heterogeneity within the two price sensitivity groups. Importantly, using these estimates the proportion of the overall distribution within the positive domains falls to less than 5 percent (representing a reduction of almost 60 percent with a theoretically inconsistent sign). The remaining parameters are estimated with similar significance and magnitudes as in the previous models. However, we remark that the coefficients of variations tend to be of a smaller magnitude.

Turning to our WTP space models, Model 5 assumes a continuous Normal distribution for the Cost parameter. The mean of this distribution is found to be of a similar magnitude as Model 3, 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, with the exception of Fence the mean WTP estimates for all parameters are significantly different from zero. The non-Cost attributes also have significant standard deviations. Similar to Model 4, in Model 6 we specify a mixture of Normals for the Cost attribute, the means and standard deviations of which are all found to be significant. We remark that the results for this parameter are somewhat different to those obtained in Model 4. We find that the majority of respondents ($\pi = 0.672$) are associated with a low price sensitivity distribution (which is analogous to the result attained in Model 2). While the mean WTP estimates retrieved from Model 6 are similar to those attained under Model 5, we note that, while significant, the standard deviations are relatively smaller than those under Model 5. While our WTP space models achieve better fits over Model 1, they do not outperform the remaining preference space models. This is in line with previous WTP space models (e.g., Scarpa et al., 2008; Train and Weeks, 2005).

To illustrate our findings regarding the Cost attribute we show in Figure 2 the (unconditional) distributions of the cost parameter under Models 1–6. Models 1 and 2 have 1 and 2 mass points respectively, whereas Models 3–6 follow non-discrete distributions. Beginning with Model 2 we note that the largest mass points is close to zero. This represents respondents who are lowly price sensitivity. Whereas, the second mass point is further from zero, therefore, representing respondents' with high price sensitivities. It is interesting to note how the mass points under Model 2 compare against the single fixed point retrieved under Model 1. As expected, the fixed cost parameter obtained under Model 1 lies within the range of the points obtained in Model 2.

The distribution of the Cost coefficient on the basis of Model 3 shows that there is a considerable range in the respondent's sensitivity to price. Moreover, a considerable proportion of the distribution is located within the positive domain, which is always a potential issue when using unbounded distributions (such as the Normal) to represent the unobserved heterogeneity for the Cost attribute. As illustrated in Figure 1 given the large share of lowly price sensitive respondents implied in Model 2, this is not a surprising finding (i.e., the mass of respondents who are lowly sensitive are 'dragging' the distribution of cost into the positive

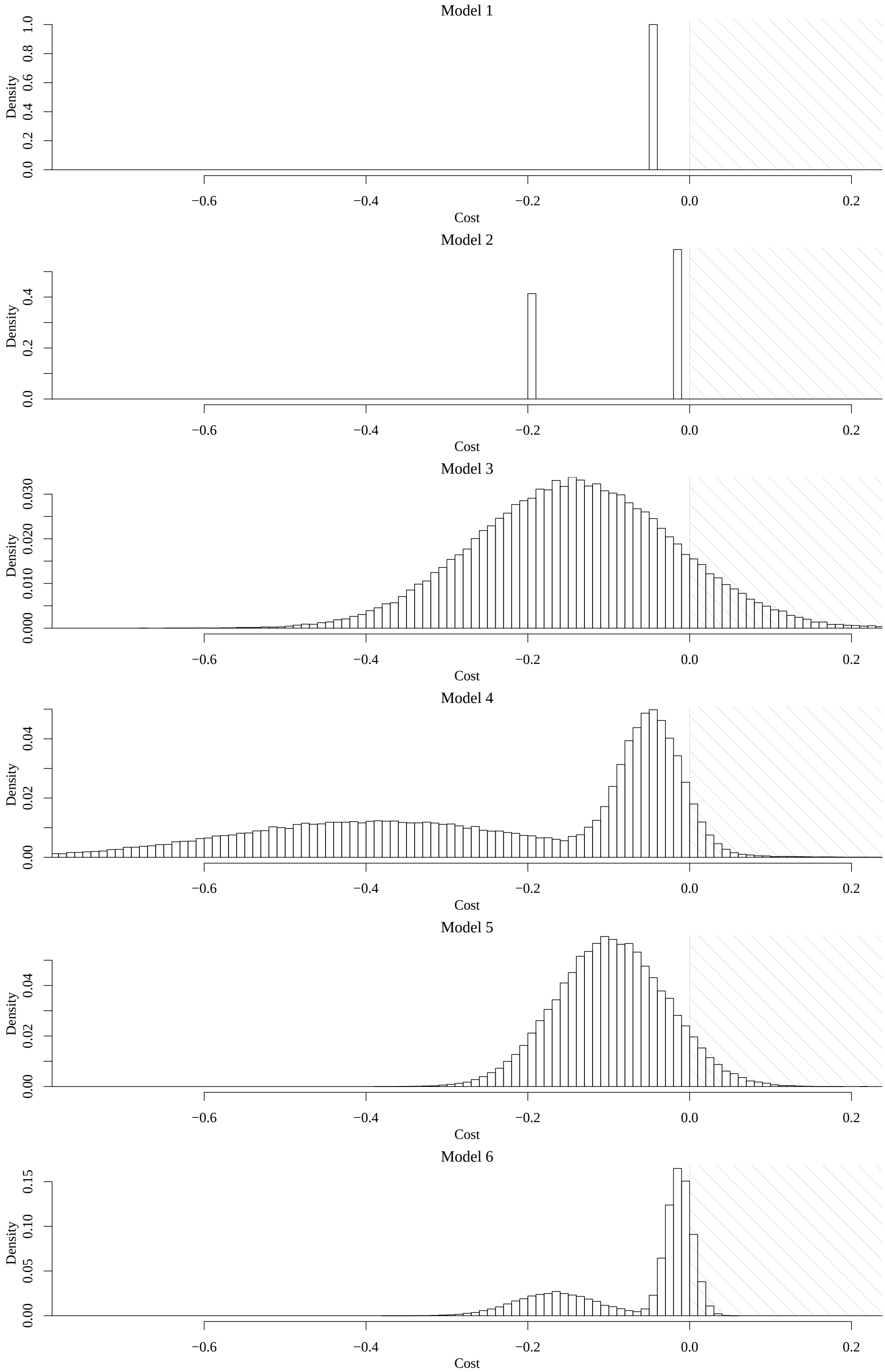


Figure 2: Comparison of (unconditional) distributions of price

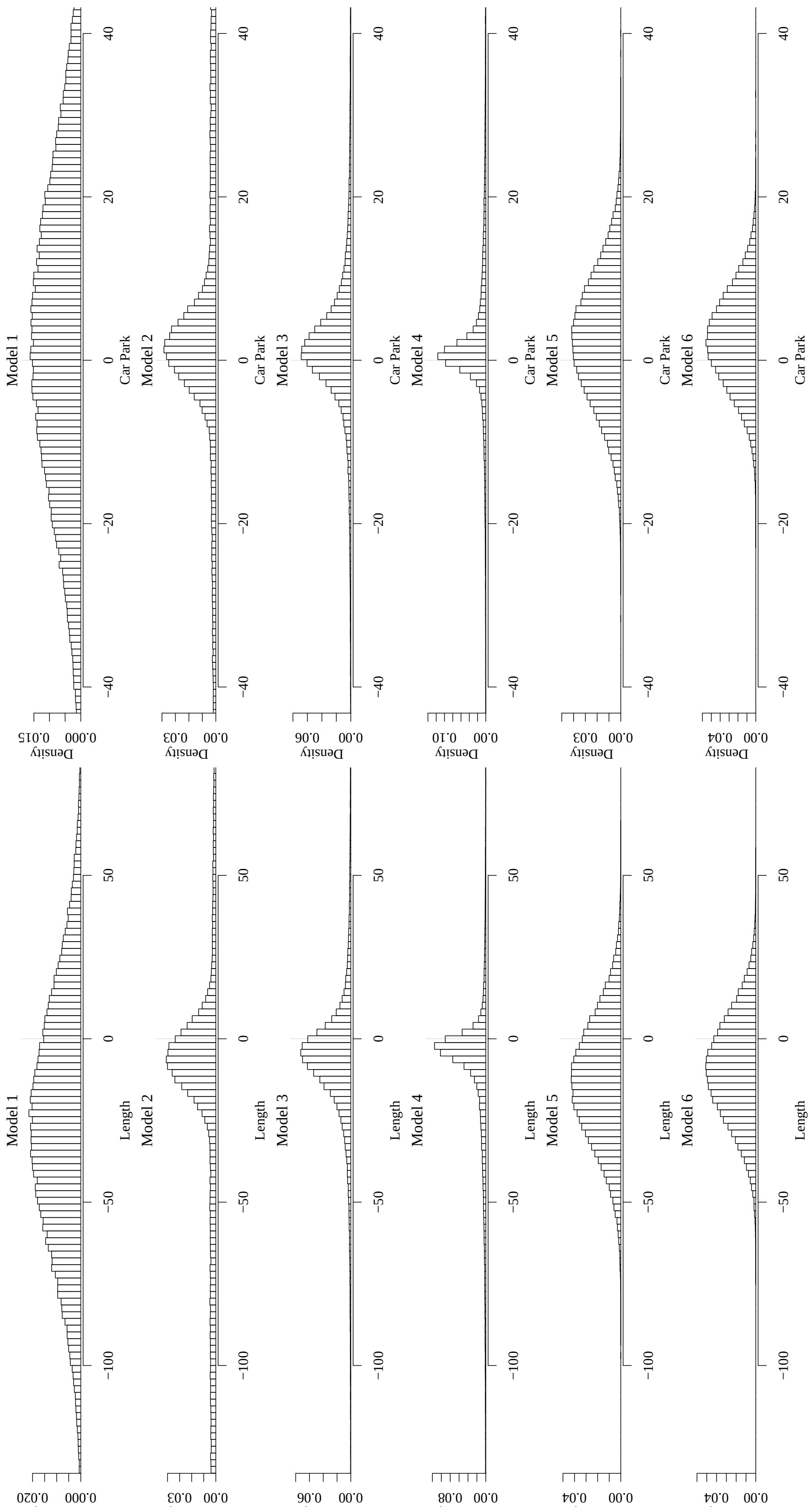
domain). As signified by the bimodal shape, it is clear that the taste intensities under Model 4 for the Cost attribute follow two distinct distributions. This is important as it demonstrates that a single continuous distribution may not adequately represent the true distribution. Whilst we acknowledge that our mixture of two Normals may still not accurately reflect the true distribution, as signified by the much superior model fit, our mixture of two Normals provides a better representation of the distribution. A further important advantage is that the overall estimated distribution is less prone to be sensitive to masses with values close to zero—resulting in a smaller share of the distribution in the positive domain.

Figure 2 also plots the distributions of Cost estimated for the WTP space models. Similar to Model 3, Model 5 has the same unimodal shape. However, we remark that under the WTP space specification the Cost attribute is estimated with a much tighter distribution and a smaller proportion in the positive domain. The distribution for Cost under Model 6 is similar in shape to Model 4, but again the distribution is considerably narrower.

4.2 Implications on welfare estimation

An alternative way of teasing out the effect of the distribution assumptions of price sensitivities is to consider the effects on the distributions of WTP. The histograms presented in Figure 3 shows the WTP (unconditional) distributions for each of the attributes obtained from the six models.

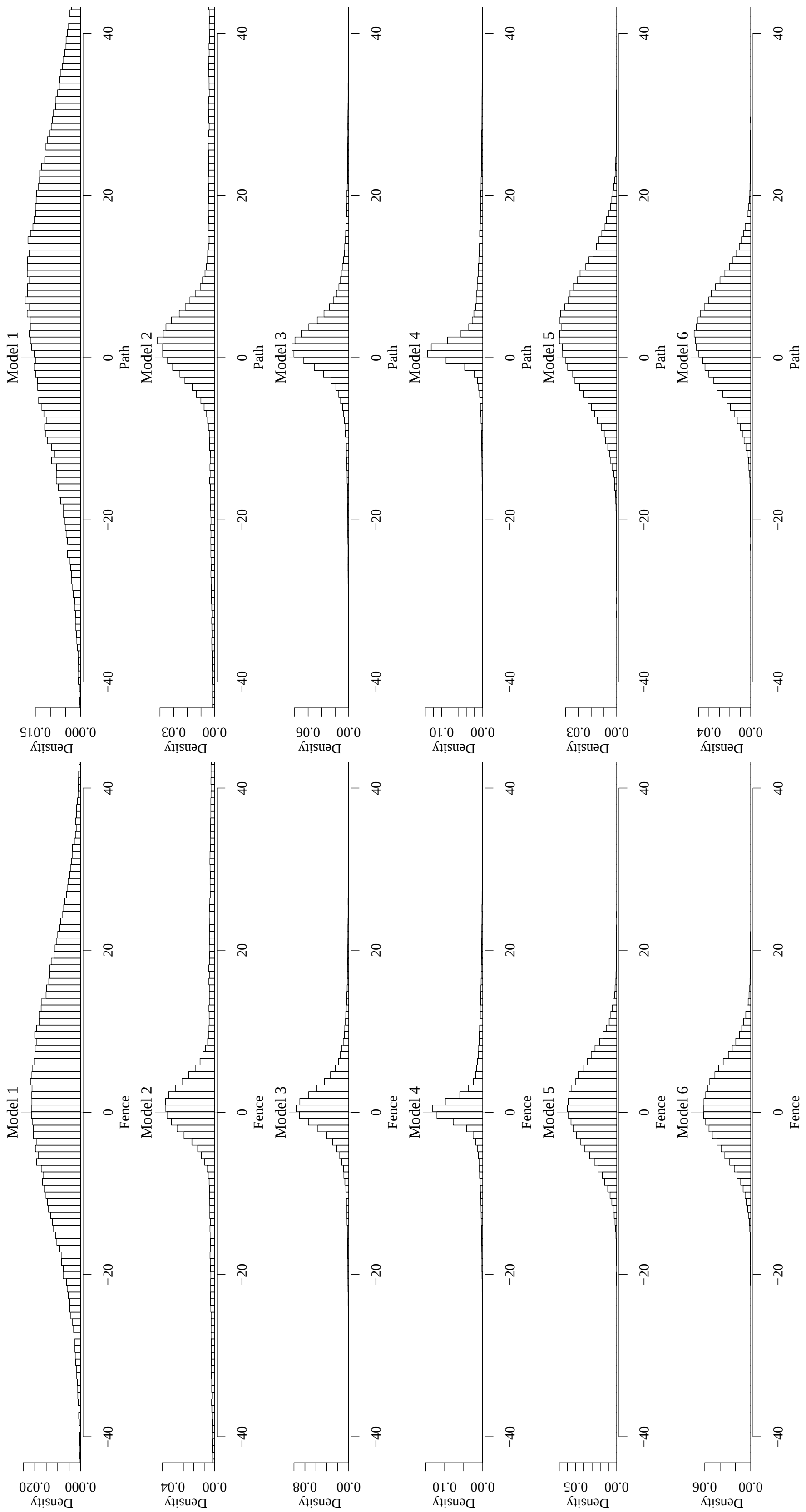
An examination of Figure 3 reveals that respondents are generally willing to pay more for trails of a shorter length (Figure 3(a)), followed those that are paved (Figure 3(d)), have car parking facilities (Figure 3(b)) and finally those that are fenced-off from livestock (Figure 3(c)). Under Model 1, since Cost is the denominator and is fixed, the distribution of WTP takes on the same distribution as the non-Cost coefficient, thus facilitating straightforward WTP estimation. But as shown, in the case of all attributes, Model 1 produces distributions that are relatively more disperse than those estimated when price sensitivities are not assumed to be homogeneous, as in Models 2–6. While the remaining preference space model provide comparable WTP distributions, we highlight a general reduction in the degree of dispersion as one moves from Model 2 to Model 4. The distribution of the WTP estimates obtained from our WTP space models are both quite similar to each other (albeit with Model 6 producing slightly tighter distributions) —indicating that the distributions of WTP estimated under our WTP space models are more robust and less sensitive to misspecification of the Cost parameter. In comparison with the preference space models (except for Model 1) they tend to have wider confidence intervals.



(a) (Unconditional) WTP distributions for Length

(b) (Unconditional) WTP distributions for Car Park

Figure 3: Comparison of (unconditional) WTP distributions



(c) (Unconditional) *WTP* distributions for Fence

(d) (Unconditional) *WTP* distributions for Path

Figure 3: Comparison of (unconditional) *WTP* distributions (con'd)

5 Conclusion

This study was designed to provide straightforward insight into the rural public's preferences for attributes of alternative farmland walking trails and as addressed in this paper, to assess the implications of distributional assumptions for the cost coefficient. To this end, we compare six models, each with a different specification for the Cost attribute. We begin with a mixed logit model with a fixed Cost coefficient, then we estimate a model in which Cost is specified with two discrete values. In the third specification we estimate Cost with a Normal distribution. In our fourth model we specify the Cost as having a mixture of Normals. Our final two models use the same specification of cost as the latter two models, but we estimated the models in WTP space.

Results in this paper show that the manner in which the heterogeneity in price sensitivities is handled is important. We show that incorporating heterogeneous price sensitivities leads to large improvements in model fit versus the relatively common approach in the non-market valuation literature where sensitivities are assumed to be homogeneous. We demonstrate the drawbacks of allowing the Cost to take on discrete points resulting in a small number of homogeneous groups, whilst specifying a continuous distribution is sensitive to extreme taste intensities and assumes that every respondent lies within the same distribution. We show that our mixture of Normals provides a very suitable means for accommodating respondents with high and low price sensitivities. Such a specification also leads to improvements in model fit and importantly a more realistic representation of heterogeneity associated with the Cost attribute. Importantly, this approach leads to a smaller proportion of the WTP distribution in the positive domain. Furthermore, it leads to much tighter WTP distributions. This overcomes a commonly found problem when estimating mixed logit models in preference space using unbounded distributions. Our models estimated in WTP space suggest that the potential misspecification of the Cost parameter does not have a large bearing on the retrieved WTP distributions. Overall therefore, our results highlight the need to assess the distributional assumptions associated with the cost attribute in environmental valuation studies.

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