Combining discrete and continuous representations of preference heterogeneity: a latent class approach

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Abstract: This paper investigates heterogeneity in preferences for forest recreators in Mallorca, Spain. We develop a latent class approach combining discrete and continuous representations of tastes and compare it with the conventional latent class and random parameter logit approaches. We investigate the performance of the discrete-continuous model by comparing welfare estimates and predictive accuracy. The discrete-continuous model outperforms latent class and mixed logit approaches when comparing goodness-of-fit and in-sample site-choice forecasts. We find that the discrete-continuous model for preference heterogeneity reveals variation among individuals' preferences and WTP, and for some policy changes our results reveal striking differences in means and distributions of WTP.

Keywords: Travel Cost Method, latent class model, random parameter model, recreation demand, forests.

JEL Classification: C25, C23, Q26, Q51

Resumen: En este artículo se investiga la existencia de heterogeneidad en las preferencias de los visitantes de áreas recreativas situadas en zonas forestales de Mallorca, España. A este fin, se desarrolla un modelo de clases latentes que combina representaciones discretas y continuas de las preferencias de los individuos que, al mismo tiempo, se compara con el modelo convencional de clases latentes y con el modelo de parámetros aleatorios. El funcionamiento del modelo discreto-continuo se evalúa mediante la comparación de las medidas de bienestar y la precisión de las predicciones proporcionadas por cada modelo. Así, al comparar la bondad de ajuste y las predicciones de las probabilidades de visita de cada área recreativa, el modelo discreto-continuo mejora las demás especificaciones (modelo de clases latentes y de parámetros aleatorios). El modelo discreto-continuo revela la existencia de heterogeneidad en las preferencias y en la disposición a pagar (DAP) hallándose, para determinados escenarios de política ambiental, diferencias sorprendentes en las medias y las distribuciones de las DAP.

Palabras clave: Método del Coste de Viaje, modelo de clases latentes, modelo de parámetros aleatorios, demanda recreativa, bosques.

Clasificación JEL: C25, C23, Q26, Q51

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1. Introduction

The random utility model (McFadden, 1974) is widely used to measure individual preferences over discrete alternatives (see for example, Haab & McConnell, 2002; Phaneuf & Smith, 2005). While conventional logit specifications (e.g. conditional and nested logit models) have dominated the recreational demand literature (Ouma et al., 2007; Hynes et al., 2008), recently models have been developed to test for preference heterogeneity across individuals (Provencher et al., 2002). The study of preference heterogeneity has become an important focus in the choice modeling and recreation demand literature (Train, 1998; Provencher et al., 2002; Shonkwiler & Shaw, 2003; Provencher & Bishop, 2004; Morey et al., 2006). Researchers have found that when heterogeneous preferences are not properly accounted for, valuable information is discarded and inconsistent estimates and biased welfare measures are obtained (Bhat, 1997; Bhat & Castelar, 2002; Hess et al., 2005; Hynes et al., 2008).

In this context, the computing revolution of the last 20 years, and the consequent generalization of simulation methods (e.g. simulated maximum likelihood estimation), has allowed researchers to estimate models with more flexible specifications that overcome the potentially restrictive assumptions implicit with conventional logit models (Morey & Rossmann, 2003; Train, 2003). Two predominant approaches for dealing with preference heterogeneity have been developed: the Random Parameter Logit (RPL) and the Latent Class model (LC) (Andrews et al., 2002; Adamowicz, 2004; Ouma et al., 2007).

The RPL introduces taste variation by assuming that each member in the sample can have a different set of utility parameters (Revelt & Train, 1998; McFadden & Train, 2000; Phaneuf & Smith, 2005). In this way, this specification provides an elegant way to accommodate preference heterogeneity using a continuous distribution for individual tastes (Morey & Rossmann, 2003; Provencher & Moore, 2006). While the appeal of handling underlying heterogeneity is an attractive feature of the model, the analyst must choose a tractable parametric form for the distribution of each random coefficient and this choice of distribution inadequately capture heterogeneous preferences in the presence of different groups of individuals with different tastes (see Hensher & Greene, 2003; Lenk & DeSarbo, 2000; Scarpa & Thiene, 2005).

The LC (finite mixture) approach accounts for preference heterogeneity in a different way by assuming that the sample of respondents arises from a given number of groups,sometimes referred to as classes or segments (Gupta & Chintagunta, 1994; Boxall & Adamowicz, 2002; Shonkwiler & Shaw, 2003; Provencher & Bishop, 2004). Although this discrete representation of taste variation is not well designed to handle within-group heterogeneity (Andrews et al., 2002), it provides an intuitive interpretation of variation across segments in the population, presenting useful information about the distribution of welfare effects associated with policy changes (Milon & Scrogin, 2006; Patunru et al., 2007). Despite these advantages, empirical evidence shows that the use of the LC specification might over-simplify the real preferences of the population, especially when a small number of classes is defined and the underlying distribution of preferences is, in fact, continuous within classes (Allenby & Rossi, 1998; Wedel et al., 1999).

Beyond the advantages and disadvantages of both approaches, the debate over continuous (RPL) versus discrete (LC) representation of preferences is still open within the discrete choice literature (Wedel et al., 1999, Andrews et al., 2002). While the RPL model is more powerful in accommodating taste variation, the model can not identify the sources of preference heterogeneity. For this reason, many researchers have implemented the LC model (Provencher et al., 2002; Greene & Hensher, 2003; Ouma et al., 2007).[1]

The underlying assumption of within-group homogeneity in LC models remains as an important unresolved issue in the literature (Lenk & DeSarbo, 2000). It is unlikely that all individuals with identical socioeconomic characteristics will have the same preferences and, hence, the assumption of within-group homogeneity is too restrictive to represent adequately the preferences of recreators (Wedel & Kamakura, 2002). Underscoring this point, Allenby et al. (1998) remark that the extent of heterogeneity is much greater than that measured by LC and indicates that further research is needed to improve the modeling of taste heterogeneity.

This paper suggests a hybrid modeling approach combining discrete and continuous representations of preferences to overcome the limitations of the conventional RPL and LC models. Following the work of Lenk & DeSarbo (2000), a random distribution of taste coefficients is integrated over the segments of a LC specification. In this way, the Latent Class - Random Parameter Logit model (LC-RPL) is first applied in a recreational demand

[1] The sources of taste heterogeneity are often related to socioeconomic characteristics, attitudes, perceptions, social influences and past experiences (Boxall and Adamowicz, 2002).

setting to account for taste heterogeneity in two ways: (1) identifying different behavioural groups as a function of socioeconomic characteristics and (2) considering taste diversity among individuals in the same group (within-group heterogeneity). The LC-RPL captures the best features of both the LC and the RPL models becoming more parsimonious than the former and more flexible than the later. Consequently, by allowing for taste variation across individuals in the same group, this new approach provides an additional insight on preference heterogeneity and a richer interpretation of the distribution of welfare effects of policy changes across the population. Furthermore, the LC and RPL models are special cases of the more general LC-RPL model.

A database of recreational trips to forest sites in Mallorca (Spain) has been used to compare the empirical performance of this new approach to common estimation approaches in recreational demand modelling (conditional logit, RPL, and LC models). Comparison of goodness-of-fit measures and in-sample forecasts across specifications provide information on model performance. We also compare the welfare effects of two policy scenarios, a quality increase and site closures, to illustrate whether Willingness-To-Pay (WTP) and its distribution across individuals significantly differs between alternative representations of taste heterogeneity in choice modelling.

The paper is structured as follows. The theoretical background of random utility model underlying the LC-RPL is developed in the next section. The data and the rationale behind preference heterogeneity amongst Mallorcan forest recreators are presented in section three. Section four outlines model estimates. Results of WTP for various policy scenarios are provided in section five and, finally, some conclusions and directions for future research are presented in section six.

2. Model

Following the development of the conventional LC specification, the LC-RPL model assumes the existence of K segments or groups in the sample of N respondents, where K is exogenously defined by the analyst. The individual's utility functions can vary between these segments (Hynes et al., 2008). However, as these classes are latent, not observable by the analyst, a probabilistic equation explaining the assignment of each individual n into the K segments has to be defined.

Although a semi-parametric form based only on a constant term can be used to specify the membership probability (Scarpa & Thiene, 2005), the most common specification is implemented with a set of socioeconomic covariates (Boxall & Adamowicz, 2002; Provencher et al., 2002)[2]. Using a multinomial logit formulation, the probability that individual n belongs to segment k can be written as a function of its socioeconomic variables z_n and the vector of estimated coefficients θ_k related to that specific segment (Bhat, 1997):

$$\pi_{nk} = \frac{e^{\theta_k' z_n}}{\sum_{m=1}^{K} e^{\theta_m' z_n}} \qquad [1]$$

Given the membership to group k, the LC-RPL site-choice probabilities follow the random utility framework. The individual chooses the alternative yielding the highest level of utility from a set of i=1,...,I known and mutually exclusive possibilities on a given choice occasion (Ben-Akiva & Lerman, 1985). Assuming that the error components of this equation are independent and identically distributed as Type I extreme value, the probability that individual n chooses alternative i, conditional on belonging to taste group k, takes the familiar logit form (Hensher & Greene, 2003):

$$\pi_{ni|k} = \frac{e^{\beta_{nk}' x_{ni}}}{\sum_{j=1}^{I} e^{\beta_{nk}' x_{nj}}} \qquad [2]$$

where x_{ni} represent the vector of attributes associated with each alternative and β_{nk} the vector of estimated coefficients. Note that, instead of assuming a fixed vector of coefficients for all subjects in segment k, a set of individual specific coefficients (β_{nk}) is used in each segment, accommodating preference heterogeneity across individuals belonging to that group (Lenk & DeSarbo, 2000). Following the specification of the conventional RPL, utility coefficients vary randomly across individuals within the same segment according to a specific distribution defined by the researcher. However, as the analyst does not observe these coefficients, it is necessary to integrate the logit formula in expression [2] over all possible values of β_{nk} (Train, 2003):

$$\pi_{ni|k} = \int \left(\frac{e^{\beta_k' x_{ni}}}{\sum_{j=1}^{I} e^{\beta_k' x_{nj}}} \right) f(\beta_k) d\beta_k \qquad [3]$$

[2] We have estimated this semi-parametric form for both the LC and LC-RPL models. The results of these models indicate that the membership class probabilities were not well defined with this specification. For the sake of brevity, these results are not reported here but are available from the authors.

At this point, the researcher has to assume a distribution for β_{nk} and estimate the parameters of such distribution that, in most applications, has been specified as normal $\beta \sim N(b,W)$ or lognormal $ln\,\beta \sim N(b,W)$ with mean b and covariance W (Train, 1998, 1999; McFadden & Train, 2000; Meijer & Rouwendal, 2006). Finally, the unconditional probability that individual n chooses i can be written from equations [1] and [3]:

$$\pi_{ni} = \sum_{k=1}^{K} \pi_{nk} \pi_{ni|k} \qquad [4]$$

Therefore, following Greene & Hensher (2003); Thacher et al. (2005); Aldrich et al. (2007), the log-likelihood function reduces to a weighted average of the log-likelihoods of the K latent classes:

$$LL = \sum_{n=1}^{N} ln\left[\sum_{k=1}^{K} \pi_{nk} \left(\prod_{i=1}^{I} \left(\pi_{ni|k}\right)^{y_{ni}}\right)\right] \qquad [5]$$

where π_{ni} and $\pi_{ni|k}$ are the membership and site-choice probabilities from equation [1] and [3] and y_{ni} equals one when the nth individual chooses alternative i and 0 otherwise. As the solution to expression [5] involves the evaluation of a multiple-dimensional integral which does not have a closed-form, the estimation of such model requires the use of simulation methods (Bhat, 1998; Revelt & Train, 1998).

Finally, note that the LC-RPL with only one class is equivalent to the conventional RPL model. At the same time, if several classes are implemented assuming within-group homogeneity, the model collapses to the traditional LC specification. If only one class characterized by homogeneous preferences is considered, the LC-RPL model collapses to the Conditional Logit (CL) model.

3. Data

For the site choice models, we use one-day forest recreational trips in the Island of Mallorca (Spain). The 59 forest sites that have been identified within the 153,115 hectares of the study area are quite diverse from both a geographical and recreational perspective. Using a geographical information system, information regarding environmental characteristics and recreational facilities that provide these sites has been collected from fieldwork inventories and existing data sets (e.g., the Balearic Islands topographic map from the Balearic Island Government, the National Institute of Metereology and the National Forest Inventory collected by the Ministry of Environment).

For data on recreation behavior, we use the regional-wide survey administrated to 1043 individuals providing a random sample of Mallorcan residents that provides for variation in individual socioeconomic characteristics and the types of outdoor recreation typical of residents. Mallorcan forest recreation trips are characterized by individuals with distinct socioeconomic profiles, types of forest recreation activity, and environmental site-specific attributes providing for an excellent setting for investigating preference heterogeneity and to examine whether diversity of tastes for on-site attributes may lead to different WTP for various forest policies.

The residents included in this population-specific sampling scheme were randomly chosen and surveyed at their home by trained interviewers. After testing the questionnaire in a pilot survey, the final version was administrated from April to July 2006. It was divided in different sections collecting data regarding number of trips, visited sites, activities undertaken in the site (hiking, picnicking, going for a walk, camping, observing the flora and the fauna, adventure sports as biking, climbing, etc.) and socioeconomic information about the respondent (income, age, place and year of birth, attained level of studies, occupation, etc.).

To compute the travel cost variable from each trip origin to the 59 available sites, data on means of transport, party size, on-site time and other costs associated with the visit was also gathered. In addition, travel time and distance have been calculated from the Mallorcan road map at scale 1:25,000 and Teleatlas digital data. When more than one route was available for a specific individual, it has been assumed that the shortest one was chosen. The mileage cost and the opportunity cost of driving time have been jointly considered to estimate the travel cost.[3]

In the prior 12 months previous to the survey, 80.63% of the sample (841 respondents) had taken one or more trips to forests. Additionally, those individuals who had visited forests took an average of 10 trips each. Going for a walk was the most popular activity in forests (40.90%), followed by hiking (24.85%), picnicking (22.95%), adventure sports (6.66%) and other activities (4.64%). The mean age in the sample was 44 and the average monthly income was 950 euros. 92.43% of sampled residents were Spanish and

[3] The mileage cost has been set to €0.19 per kilometre according to the official cost per kilometre dictated by the Spanish Government in 2005. For opportunity cost of time, we use the lower bound often used in literature, consisting of one-third of the individuals wage (Englin & Shonkwiler, 1995; Phaneuf & Smith, 2005).

48.21% men, while 35.57% had completed primary studies, 37.87% secondary studies and 26.56% tertiary studies. As for employment status, 63.57% were employed, 4.03% were unemployed, 10.45% were housewife or househusband, 15.44% were retired and, lastly, 6.51% were students.

4. Results

The econometric results for the LC-RPL model defined in section two are presented in Table 1. For comparison, the conditional logit (CL), RPL and LC models have also been estimated and included in Table 1 as benchmark cases. All estimates are obtained by simulated maximum likelihood (or maximum likelihood) using MATLAB. For simulated log-likelihood functions we use 200 replications per observation.[4,5]

Table 1: Coefficients estimates (standard errors in parentheses)

Variable	CL		RPL		LC		LC-RPL	
Site-choice equation (class 1)								
Travel cost	-0.2309	(0.0113)	-0.2362	(0.0118)	-0.8237	(0.0859)	-0.8287	(0.0860)
Picnic facilities	0.2983	(0.0783)	0.2952	(0.0783)	0.4329(*)	(0.1681)	0.4745	(0.1673)
Kilometres of roads	0.1809	(0.0157)	0.1741	(0.0157)	0.2954	(0.0359)	0.2889	(0.0358)
Landscape quality (mean)	0.1395	(0.0302)	-0.7675	(0.5350)	-2.2615	(0.6941)	-3.1525	(1.0140)
Landscape quality (s.d.)	-		1.5636	(0.4032)	-		2.0262	(0.5065)
Site-choice equation (class 2)								
Travel cost					-0.0580	(0.0195)	-0.0541	(0.0202)
Picnic facilities					0.1616(+)	(0.1226)	0.1323(+)	(0.1244)
Kilometres of roads					0.1057	(0.0232)	0.0964	(0.0232)
Landscape quality (mean)					-1.7902	(0.2918)	-2.4384	(0.6108)
Landscape quality (s.d.)					-		1.3992	(0.4654)
Membership equation (class 1)								
Intercept					1.7800	(0.4379)	1.8910	(0.4589)
Income					-0.0647	(0.0189)	-0.0627	(0.0191)
City					-1.8799	(0.2819)	-1.9019	(0.2839)
High-education					-1.0504	(0.2930)	-1.1162	(0.3038)
Natural areas					0.4456(**)	(0.2607)	0.4592(**)	(0.2641)
Log-likelihood function		*-3146.1239*		*-3144.3707*		*-2994.4493*		*-2990.1738*
Restricted log-likelihood		*-3429.2090*		*-3429.2090*		*-3429.2090*		*-3429.2090*
McFadden-R^2		*0.0826*		*0.0831*		*0.1268*		*0.1280*
Adjusted McFadden- R^2		*0.0814*		*0.0816*		*0.1230*		*0.1237*
In-sample forecasts mean-squared error		*0.0002692*		*0.0002716*		*0.0002200*		*0.0002173*

All estimated coefficients are statistically significant at a 1% level except those denoted by (*) and (**) which are significant at 5% and 10% level respectively. Non-significant coefficients are denoted by (+).
Source: own elaboration.

[4] Our code benefited greatly from Matlab code from the Workshop "Revealed Preferences Outside Markets: Micro-econometrics in Environmental Economics" organized by Dan Phaneuf & Kerry Smith.

[5] A sensitivity analysis for starting values has been performed to examine the convergence properties of the models. Only when the starting values have been set sufficiently far away from the solution (and with opposed signs) the model has failed to converge. Such converge problems have been found in both, the RPL and the LC-RPL models.

For model specification, we consider travel cost and a large set of environmental attributes and recreational facilities characterizing forest sites. We include four variables to capture environmental quality of sites in the final specifications.[6] The site-specific variables are 'travel cost', the availability of 'picnic facilities' in the site, the 'kilometres of roads' in the site (used as a proxy measure of accessibility inside the forest area), and a 'landscape quality' index that brings into consideration the biotic (forest composition, arboreal cover classification, burned forest areas, etc.) and anthropogenic elements (infrastructures, urban areas, farms, etc.) present in the site and its surroundings.[7]

The signs and magnitudes of coefficients conform to expectations and, in general, their interpretation across models is similar. While 'travel cost' has a negative effect on the probability of site-choice as shown by the negative sign of its coefficient, the availability of 'picnic facilities', the 'kilometres of roads' in the site and the 'landscape quality' are desirable characteristics for recreationists and, hence, increase site-choice probability ceteris paribus.

For the RPL and the LC-RPL specifications, alternative distributions (normal, lognormal, etc.) have been investigated for the random parameter coefficients. However, for our data, only the introduction of 'landscape quality' as a random parameter significantly improves the model fit. The rationale behind allowing for randomness in the site quality coefficient is motivated by subjective information about quality across individuals, variation of quality, and variation of the recreational interests of each individual, their environmental attitudes, education, etc.

All coefficients have been included as fixed in both models with the exception of the 'landscape quality' attribute, specified as random following a lognormal distribution.[8] The values related to the 'landscape quality' variable provided in Table 1 correspond to the estimated mean and standard deviation parameters of a lognormal distribution. Consequently, implicit in this lognormal distribution is the assumption that while preferences vary over individuals, everyone prefers more to less 'landscape quality' in the visited site. In fact, the highly significant standard deviation parameter of the 'landscape quality' variable indicates that preferences towards this attribute do indeed vary across the population. Overall, the coefficients estimated from the RPL specification are similar to those of the CL model.

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[6] While alternative specifications with more site-specific attributes were estimated, the final model includes only the key attributes being the most significant determinants of choice overcoming significant collinearity issues.

[7] The details of how this index is calculated can be found in (Bujosa & Riera, 2009).

[8] The lognormal distribution has traditionally been used in variables which coefficient is expected to have the same sign for all individuals in the sample (Revelt & Train, 1998; Train, 1999). In this case, it is quite reasonable to assume that 'landscape quality' is a desirable feature with a positive effect on utility for all respondents.

Although the RPL model allows the identification of heterogeneity in preferences for 'landscape quality', this specification does not provide any information on the source of such diversity of tastes. In contrast, the LC model allows for the identification of different behavioral groups within the sample of respondents. Unfortunately, the determination of the optimal number of classes or segments with different preferences is not endogenous to the estimation process and statistical inference in the classic sense is not possible for deciding the optimal number of classes (Thacher et al., 2005; Hynes et al., 2008).[9] Although different statistics based on the information criteria developed by Hurvich & Tsai (1989),[10] as well as the entropy index,[11] have commonly been used to provide some guidance to the analyst to decide the number of segments or classes (Thacher et al., 2005), the choice of number of classes must also consider other issues as the significance of the estimated parameters and the meaningfulness of the parameters and their signs (Scarpa & Thiene, 2005; Morey et al., 2006).

The statistical analysis of our data shows as recreationists split into two groups with a clear differentiated behavioural profile. If more than two classes are included in the model, the additional groups represent only a small portion of the total respondents and the lack of significance of their parameters precludes their association to a specific behaviour. In addition, the optimization process of the simulated log-likelihood function of the LC-RPL with more than two classes for our data, quite often, has failed to converge. For all these reasons and to facilitate comparison between models, only two classes have been included in the LC and LC-RPL specifications.

In looking across all models, some general results emerge. First, recreators prefer sites that are less costly to access, higher quality sites, and sites with better amenities, regardless of model or tier.[12]

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[9] The conventional specification tests such as the likelihood ratio or the Wald tests do not satisfy the regularity conditions for a limiting chi-square distribution under the null within this context (Scarpa et al., 2007).

[10] Given the log-likelihood of the model at convergence *LL*, the number of parameters included in the specification *J* and a penalty constant δ, the information criteria statistic *C* is defined as $C=2LL+J\delta$ (Scarpa et al., 2007; Hynes et al., 2008). Consequently, different statistics can be derived under different values of the penalty constant. For $\delta=2$ the Akaike Information Criteria (AIC) is obtained, $\delta=ln(N)$ the Bayesian Information Criteria (BIC) is derived, and for $\delta=2+2(J+1)(J+2)/(N-J-2)$, the corrected AIC (crAIC) is obtained.

[11] The entropy index is a measure of good segregation across groups that takes the form (Wedel & Kamakura, 2000; Morey et al., 2006):

$$\varepsilon = 1 - \frac{\sum_{n=1}^{N}\sum_{k=1}^{K} -\pi_{nk}\, ln(\pi_{nk})}{N\, ln(K)}$$

[12] The only exception to this is in the LC model, tier 2 the sign on picnic is positive but not significant.

From the results of the LC model, class 1 shows a high sensitivity to travel expenses and the presence of roads as compared with class 2. Furthermore, the presence of picnic facilities is an attractive feature for individuals in class 1, but not for class 2. Conversely, the landscape quality of the forest site is desirable for respondents in class 2, while people in class 1 do not exhibit as strong preferences. In sum, the pattern of tastes of class 1 is associated to those individuals looking for forest areas close to home equipped with recreational facilities to undertake intensive recreational activities such as picnicking. In contrast, class 2 is representative of those individuals with a more naturalistic attitude, looking for a direct contact with the natural beauty of forests and undertaking non-intensive recreational activities such as hiking, going for a walk, observing the flora and fauna, etc. Accordingly, such individuals prioritize landscape quality to accessibility and do not care about recreational facilities relative to class 1.

The estimated coefficients of the membership equation are also reported in Table 1 providing information about the sources of taste heterogeneity across both segments. The membership coefficients for the second group have been normalized to zero to be able to identify the remaining coefficients of the model and, hence, the membership equation for class one has to be evaluated relative to group two. The final specification of the membership equation includes a constant term and variables describing the socioeconomic background of individuals. As pointed out by Bhat (1997), the constant in the membership equation do not have any substantive interpretation beyond its contribution in the probability mass assigned to each segment.

For the membership probabilities, the negative sign of the dummy variables 'income', 'city' and 'high-education' indicate that those individuals with higher income, a higher level of education or living in a city (instead of in a small village) are more likely to belong to group 2. These results are reasonable when compared with the behavioural profiles identified in the site-choice equation of both classes: higher income and educational level of people in the second group is consistent with the lower sensitivity of these respondents to travel costs and their higher interest for landscape quality. Similarly, the positive sign of the 'natural areas' dummy variable shows as respondents who considered that the provision of natural areas was acceptable are more likely to be in group 1. For the estimated LC model the membership probabilities averaged across all individuals in the sample place 41.48% weight on group 1 and the remaining 58.52% to group 2.

Finally, we turn to the coefficient estimates for the LC-RPL specification. Note that, while the LC specification restricts within group heterogeneity, the LC-RPL model allows for preference heterogeneity through the 'landscape quality' random parameter. Then, although LC-RPL coefficients are similar to those of the LC model, the estimated variance for the 'landscape quality' variable in both tiers suggests that, even though significant variation can be explained by socioeconomic data, an important part of the variation remains unexplained. Concerning the class membership probabilities, they are quite similar to those of the LC model with a 42.93% for group 1 and 57.07% for group 2.

Three primary conclusions can be drawn about the models presented in Table 1. First, the magnitudes and signs of the coefficient estimates do not show big differences across models. Second, based on likelihood ratio tests, the LC-RPL statistically dominates the other specifications in terms of goodness-of-fit.[13] Third, from mean-squared errors calculated for in-sample forecasts, the LC-RPL specification provides the best prediction of observed site-choice probabilities, where the LC-RPL outperforms the CL, RPL, and LC by 19.3%, 19.9%, and 16.3% respectively.

5. Welfare Estimates

Since a common use of recreation demand models is in the estimation of welfare effects related to environmental policy changes we next investigate the implications of heterogeneity on welfare measures for two example policies. Based upon Small & Rosen (1981) and Hanemann (1982, 1999) measures of welfare change for random utility models, the Willingness-To-Pay (WTP) is defined as the measure of the welfare change associated to an increase (decrease) of some attribute present in the indirect utility function of an individual. With constant marginal utility of income (for each individual), the individual-specific WTP becomes:

$$WTP_n = \frac{1}{\beta^{TC}}\left[ln\left(\sum_{i=1}^{I^0} e^{\beta' x_{ni}^0} \right) - ln\left(\sum_{i=1}^{I^1} e^{\beta' x_{ni}^1} \right) \right] \qquad [6]$$

where β_{TC} is the travel cost coefficient associated with the marginal utility of income and the attributes before and after the policy change are denoted by x_{ni}^0 and x_{ni}^1, and the available sites pre and post-policy by I^0 and I^1, respectively.

[13] Two likelihood ratios tests are provided, the so-called McFadden-R^2 or Pseuso-R^2 defined by McFadden (1974) and the adjusted McFadden-R^2 suggested by Ben-Akiva and Lerman (1985). We also note that based on AIC and BIC criteria, the LC-RPL is the preferred model.

While the WTP measure in equation [6] corresponds to the conditional logit model, we estimate similar measures for the RPL (Hynes et al., 2008), the LC (Boxall & Adamowicz, 2002) and the LC-RPL. However, we include only the equation for the LC-RPL in the interest of brevity. In this model, heterogeneity enters in two ways: [1] the expected WTP is conditional on individual preferences β_n, found by integrating over the estimated preference distribution of the population within a segment, and [2] the expected WTP has to be weighted by segment membership for each individual. Consequently, we can write expected willingness to pay for individual *n* as:

$$WTP_n = \sum_{k=1}^{K} \pi_{nk} \int \left\{ \frac{1}{\beta_k^{TC}} \left[ln\left(\sum_{i=1}^{I^0} e^{\beta_k' x_{ni}^0} \right) - ln\left(\sum_{i=1}^{I^1} e^{\beta_k' x_{ni}^1} \right) \right] \right\} f(\beta_k) d\beta_k \qquad [7]$$

Using welfare measures as in equation [7], we analyze two policies for illustrative purposes. First, we investigate the welfare effects of a 25% increase in environmental quality at all sites in the choice set to illustrate how the treatment of heterogeneity might impact the willingness to pay for policies that have widespread impacts on site quality. Second, given that the impact caused by recreation demand on some forest ecosystems is significant, we analyze the welfare effects of closing the six most visited recreational sites to illustrate the case where managers may need to close heavily impacted sites to allow for natural recovery.

The welfare results of both policy scenarios are summarized in Table 2.[14] As expected, mean and median WTP (and confidence intervals) vary significantly among the estimated models and much of this variation depends on the treatment of heterogeneity. Results show that models allowing for preference heterogeneity in their specifications, in general, lead to higher mean WTP estimates. While the individual WTP for a 25% increase of landscape quality is 1.59 euros (1.96) in the RPL (LC) model, is more than 2.6 (2.12) times higher in the LC-RPL model (4.16 euros). We do not see similar differences associated with site closures. Here, the WTP in the RPL (LC) model is –83 (-1.56) euros, which is 1.9 (1.01) times higher (in absolute value) in the LC-RPL (-1.58 euros).

Taken together these findings show that the choice of modeling approach for heterogeneity is a key issue when policy guidance is needed for interventions that may impact attributes where heterogeneous preferences are thought to exist. For a scenario

[14] Confidence intervals were constructed using the Krinsky-Robb simulation method (Krinsky & Robb, 1986) using 1,000 random draws from a multivariate normal distribution, with means and covariance given by the estimated parameter vector and covariance matrix of the coefficients.

like this (scenario 1), we see that the LC-RPL, by allowing for preference heterogeneity with-in group, leads to higher WTP. To get insight into exactly how the choice of model impacts WTP, we provide histograms of the simulated distribution of WTP from the Krinsky-Robb method described above and compare the LC to the LC-RPL model.

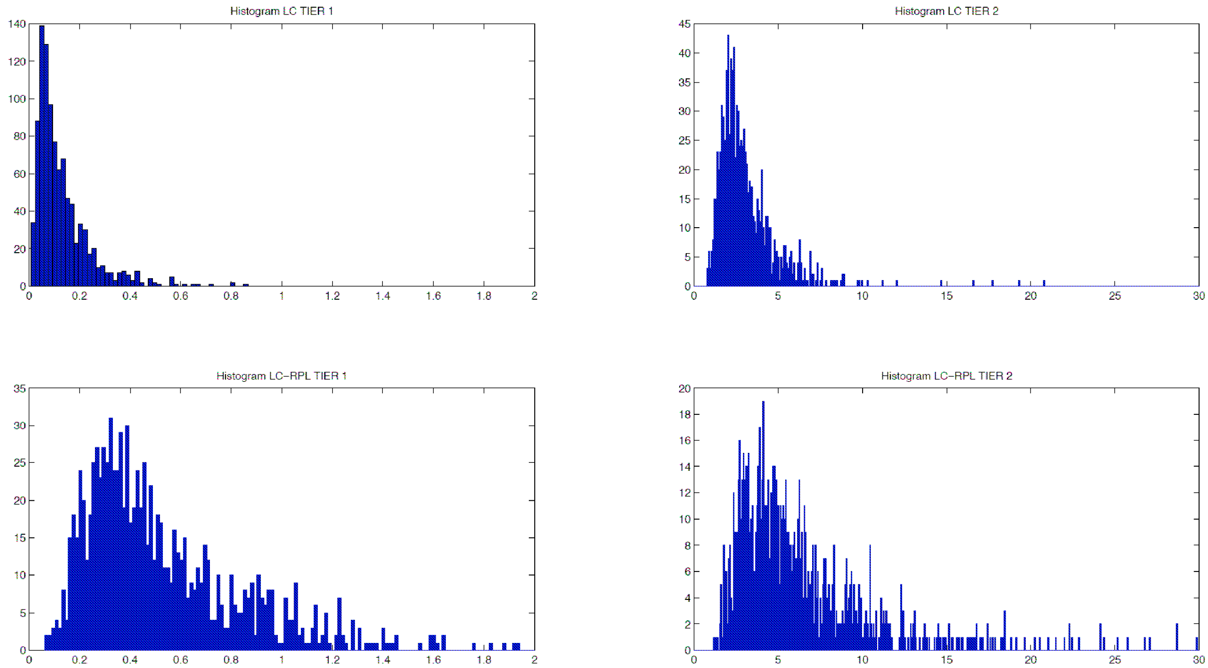
Table 2: Mean, median (in parenthesis) and confidence intervals (in brackets) expected WTP estimates*

Scenario	Model	Class 1	Class 2	Average
1) Quality increase	CL	-	-	0.5280
			-	(0.5294)
				[0.2879 – 0.7724]
	RPL	-	-	1.5888
			-	(0.9651)
				[0.5356 – 2.3870]
	LC	0.1297	3.3576	1.9645
		(0.0965)	(2.6468)	(1.6242)
		[0.0216 – 0.4287]	[1.866 – 7.6206]	[0.7811 – 4.0881]
	LC-RPL	0.5427	7.1395	4.1620
		(0.4433)	(5.1699)	(3.1413)
		[0.1533 – 1.4077]	[1.8310 – 20.7512]	[1.2893 – 10.6734]
2) Site closures	CL	-	-	-0.8623
			-	(-0.8611)
				[-0.9344 – -0.7975]
	RPL	-	-	-0.8270
			-	(-0.8279)
				[-0.8999 – -0.7494]
	LC	-0.7888	-2.1499	-1.5628
		(-0.7964)	(-2.1099)	(-1.5294)
		[-0.9010 – -0.6328]	[-5.5103 – -1.3693]	[-3.3191 – -1.1315]
	LC-RPL	-0.7530	-2.2624	-1.5804
		(-0.7608)	(-2.1893)	(-1.5311)
		[-0.8598 – -0.6095]	[-7.6055 – -1.3289]	[-4.0973 – -1.10884]

* Confidence intervals have been computed following the Krinsky-Robb method with 1,000 repetitions. WTP values expressed in euros per choice occasion.

Focusing first on the quality increase scenario, Figure 1 shows how for each tier (reported in columns) the distribution of WTP differs by model (reported in rows). The distributional effects captured by the LC and LC-RPL are consistent with the findings from previous studies (Armstrong et al., 2001) where individuals with higher income are willing to pay more for site-specific attributes. The estimated distributions are quite different and these results show that allowing for heterogeneity shifts the mass of the distribution right-ward for the LC-RPL, compared to the LC model. For example, in the second tier of the LC model 10.1% of the mean simulated WTP lie to the right of 5 euros, while in the LC-RPL over 50% are above 5 euros[15]. Figure 2, shows the same distributions for the site closure policies do not exhibit similar patterns, since differences due to the treatment of heterogeneity effectively cancels in the welfare calculation.

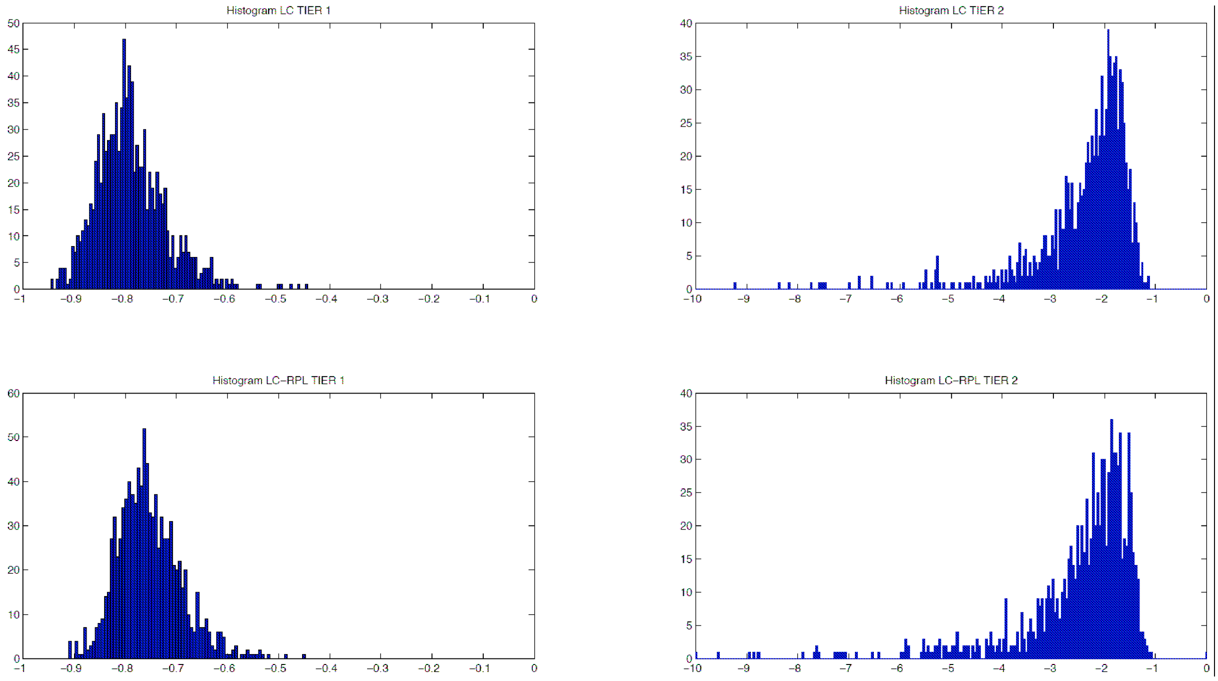
Figure 1: Histograms of the estimated individual WTP for a 25% increase in site quality



We have also formally tested for differences in distribution intra-model (across tiers) and intra-tier (across models) using the Wilcoxon non-parametric test. The results of testing for differences can be found in Table 3. The results show that significant differences exist when moving across tiers within the same model for either policy change, even for the case of closures. When moving beyond the mean welfare effect, the treatment of heterogeneity provides insight into how the population is distributed, and in the case of the LC-RPL information on the within-group distribution of preferences. Perhaps as importantly, particularly for the case of the LC-RPL, is the finding that for all but one case (the closure scenario), the estimated distributions with in are statistically distinct. In the case, of the quality change scenario, this is visually evident.

[15] The lognormal distribution may account for part of the explanation of why the distribution shifts non-symmetrically when with-in group heterogeneity is introduced, but experiments with other models show that even if normal distributions for the random quality coefficients are used these same patterns hold. These results are available from the authors.

Figure 2: Histograms of the estimated individual WTP for closure of six most visited sites



We have also formally tested for differences in distribution intra-model (across tiers) and intra-tier (across models) using the Wilcoxon non-parametric test. The results of testing for differences can be found in Table 3. The results show that significant differences exist when moving across tiers within the same model for either policy change, even for the case of closures. When moving beyond the mean welfare effect, the treatment of heterogeneity provides insight into how the population is distributed, and in the case of the LC-RPL information on the within-group distribution of preferences. Perhaps as importantly, particularly for the case of the LC-RPL, is the finding that for all but one case (the closure scenario), the estimated distributions with in are statistically distinct. In the case, of the quality change scenario, this is visually evident.

Table 3: Testing for Differences in Simulated WTP Distributions

	Distribution Comparison			
Scenario	$LC_1 - LC_2$	LC RPL_1 - LC RPL_2	LC_1 - LC RPL_1	LC_2 - LC RPL_2
Quality Increase	Reject	Reject	Reject	Reject
Closure	Reject	Reject	Reject	Accept

Beyond the statistical comparisons found in WTP between groups, the LC-RPL model confirms the hypothesis of intra-group heterogeneity by showing that the WTP is not constant across individuals in the same group. That is, people in the same group and, hence, with similar socioeconomic characteristics, have different WTP for changes in environmental attributes. While the recreationist groups identified in the LC model is useful information from an environmental management standpoint, the LC-RPL model uncovers even more information about important differences in the preferences of forest recreators. Consequently, for this study the LC model is over-simplifying the structure of preferences of individuals and likely an underestimation of the WTP for forest amenities.

6. Conclusion

Unobserved preference heterogeneity has been widely recognized as a critical issue not only for modelling choice behaviour (Allenby & Rossi, 1998; Wedel et al., 1999), but also for policy analysis (Christie & Hanley, 2008). This paper examines alternative approaches for incorporating heterogeneity in models of recreational demand. We apply a hybrid model combining discrete and continuous heterogeneity representations of tastes to capture the best features of both the LC and the RPL models. This model allows for the joint estimation of discrete segments and within segment heterogeneity providing a richer interpretation of preference heterogeneity. We compare this approach to the CL, the RPL, and the LC model.

The results reveal the existence of heterogeneous preferences for environmental attributes related to socioeconomic characteristics (income, education, place of residence, etc.) and two behavioural groups with different socioeconomic profiles are identified in the empirical application. Specifications accounting for preference heterogeneity demonstrate better performance for both, goodness-of-fit and in-sample forecasts. Models with discrete (LC) and discrete-continuous (LC-RPL) representations of heterogeneity, outperform those specifications based exclusively on continuous distributions of tastes (RPL). The LC-RPL model outperforms all models for goodness-of-fit and best in-sample predictions.

We investigate two policies –an island-wide quality change and the closure of the 6 most visited sites– finding that WTP measures vary significantly among the estimated models depending on the treatment of heterogeneity. Models allowing for higher degree of preference heterogeneity lead to higher mean WTP estimates. For example, in the quality increase scenario, the mean WTP in the LC-RPL model (4.16 euros) is 2.12 times higher than in the LC (1.96 euros) and 2.6 times higher than in the RPL model (1.59 euros). Additionally, considerable differences have been found between the two groups of recreationists identified in both models, the LC and LC-RPL, with individuals in the second group having higher income and higher WTP being an evidence of their greater concern towards environmental issues as landscape quality. In contrast, individuals in the first group are less sensitive to the policy changes investigated in this application showing a lower WTP.

Beyond merely identifying these behavioural groups, the LC-RPL has relaxed restrictions by including preference heterogeneity beyond the mean welfare effect for individuals within the same group. Such treatment of heterogeneity provides an additional insight into how the population is distributed even within the same tier and, hence, it leads to more useful and accurate WTP estimates. In fact, the results from the LC-RPL model give evidence of the heterogeneous tastes of those individuals which, sharing a similar socioeconomic profile, have been grouped in the same segment. Nevertheless, the application of our model to other study sites is needed before reaching definitive conclusions.

In sum, the LC-RPL approach developed in this paper has the potential for significantly enhancing the effectiveness of policy decisions by analysing the heterogeneous preferences of individuals in a context of recreational destination choice. The ability of the LC-RPL model to identify different groups of users, based on their socioeconomic characteristics, at the same time that allows for within group taste heterogeneity towards different environmental site attributes, can provide useful information to policy-makers in different contexts. However, more simulated and empirical studies are needed to apply this method in other datasets and, in this way, to fully understand its strengths and weaknesses for estimating choice models when heterogeneity in preferences is present.

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