Effects on Welfare Measures of Alternative Means of Accounting for Preference Heterogeneity in Recreational Demand Models

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Multiattribute-revealed preference data are used to investigate heterogeneity in a sample of kayakers for a panel of whitewater sites in Ireland. This article focuses on a comparison of preference heterogeneity using a random parameter logit model with correlated tastes and a latent class model, in terms of the implications for welfare measures of environmental quality and site-access changes. Recreationalists' skill levels are found to affect preferences in both approaches. Statistics for the estimated distribution of welfare changes for the average respondent are computed for changes in site attributes, but contrary to previous work, these are found to be of similar magnitude.

Key words: latent class models, preference heterogeneity, random parameter logit, whitewater kayaking.

For many years, the assumption that preferences are homogenous dominated revealed preference analysis of the demand for nonmarket goods albeit with some notable exceptions such as Morey (1981) and Morey, Rowe, and Watson (1993). In a seminal paper, Train (1998) emphasized that explicit recognition of taste heterogeneity is important in the estimation of destination choice random utility models to avoid bias in attribute coefficient estimates, biased welfare change measurements from site attribute variations, and ultimately poor policy decisions. In this article we analyze site choice decisions for whitewater kayakers, comparing two empirical models that have recently emerged as a way of accounting for unobserved taste heterogeneity across individuals, namely the random parameter logit (RPL) model and the latent class (logit) model (LCM). The RPL model and LCM are chosen because they have been championed as the most promising specifications to address unobserved taste heterogeneity, and yet represent fundamentally different approaches from that employed in more traditional fixed parameter logit models (Wedel et al. 1999; Greene and Hensher 2003; Morey, Thacher, and Breffle 2006).

In contrast to the approach taken by Provencher and Bishop (2004), we focus on the implications of the choice between LCM and RPL for the estimation of welfare impacts, in terms of per choice occasion consumers' surplus from changes in environmental quality and site-access conditions. We also examine differences in the distribution of welfare effects across visitors estimated from the two approaches. Following extensive specification searches we find evidence that the individual's skill level affects heterogeneity of taste in a systematic way, so we allow skill to enter both approaches in a conceptually equivalent way by making the attribute mean estimates and the membership probabilities conditional on the skill of the kayaker in the RPL and the LCM, respectively. By doing so, we find that using a latent class approach results in similar mean welfare estimates to that of an RPL. This is in contrast to previous research.

One may think of individual whitewater sites as different bundles of a given set of attributes. Taking these attributes into account, kayakers make choices from the set of all whitewater sites in deciding where to go on a particular kayaking trip. Our results indicate that kayaker preferences for recreational demand

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sites are likely to be characterized by systematic heterogeneity. In the next section we discuss the two random utility modeling approaches used in this study to analyze whitewater kayaking site choice demand, which take into account such unobserved taste heterogeneity. Following this we review previous valuation research that focus on issues of heterogeneous preferences. We then describe the design of our survey and summarize some sample characteristics. Specification testing for model estimation and selected results will be presented with attendant estimates of consumer surplus per choice occasion, as implied by our alternative models.

Methodology

The Random Utility Model (RUM) of McFadden (1974) is the standard statistical economic framework used to estimate behavioral models of site recreation choice (in a setting such as ours, this is characterized by kayaker choice between several whitewater sites with varying perceived attributes). The main idea of the RUM model is that the individual chooses from a number of alternatives (e.g., whitewater sites) and selects the one that yields the highest expected utility level on any given choice occasion. Assume that a kayaker, n, has J possible multiattribute whitewater sites from which to choose. The total utility perceived by kayaker n from visiting a candidate site i is assumed to be given by

$$(1) \qquad U_{in} = V(X_{in}, y_n - p_{in} \mid \boldsymbol{\theta}_n, z_n) + \varepsilon_{in} = V_{in} + \varepsilon_{in}.$$

Here, V_{in} is the indirect utility function from visiting whitewater site i, $\boldsymbol{\theta}_n$ is a vector of individual-specific parameters, z_n are individual-specific covariates, ε_{in} is the stochastic element of utility, X_{in} is a vector of perceived site attributes, y_n is income, and p_{in} is travel cost. Whenever the utility from visiting site i is greater than the utility from visiting all other sites $j \in J$, site i will be chosen. This leads to the following probability specification:

$$(2) \qquad \Pr(i) = \Pr(V(X_{in}, y_n - p_{in} \mid \boldsymbol{\theta}_n, z_n) + \varepsilon_{ij} \geq V(X_{jn}, y_n - p_{jn} \mid \boldsymbol{\theta}_n, z_n) + \varepsilon_{jn}), \quad \forall j \in J.$$

The RUM model can be specified in different ways depending on the distribution of the error term. If the error terms are independently and identically drawn from an extreme value distribution, the RUM model is specified as a conditional logit (CL) (McFadden 1974). This implies that the probability of choosing site j is the familiar logit with scale parameter μ, or

$$(3) \qquad \Pr(i) = \frac{\exp(\mu V_{in})}{\sum_{k=1}^{J} \exp(\mu V_{jn})}.$$

The Random Parameter Logit Model

The Random Parameter logit model generalizes the CL by allowing the coefficients of observed variables to vary randomly over people rather than being fixed. Conditional on individual tastes the choice probability is still logit, but the marginal probability across individuals requires integrating over a distribution of tastes, which needs to be specified by the analyst. The multivariate normal and its transformations are of particular appeal in this context because of their computational tractability. Assuming that individual tastes are distributed across people according to a multivariate normal, we can write $\beta_n \sim N(\bar{\beta}, \Omega)$. The variance covariance matrix Ω can be specified in a manner consistent with either independence of taste intensities (by identifying only its diagonal values), or correlation (by allowing for nonzero off-diagonal values). The unconditional probability of site selection in an unbalanced panel of recorded destination choices by kayaker n then becomes

$$(4) \qquad \Pr(i) = \int \prod_{t=1}^{t=T(n)} L_t(i \mid \boldsymbol{\beta}_n) \varphi(\bar{\boldsymbol{\beta}}, \Omega)\, d\boldsymbol{\beta}_n = \int \prod_{t=1}^{t=T(n)} \frac{\exp(\mu V_{int})}{\sum_{k=1}^{J} \exp(\mu V_{jnt})} \varphi(\bar{\boldsymbol{\beta}}, \Omega)\, d\boldsymbol{\beta}_n$$

where $T(n)$ is the number of choices observed for each respondent n, $\varphi(.)$ denotes the multivariate normal density, $\bar{\boldsymbol{\beta}}$ and Ω are the mean and variance parameters to be estimated from sample data, and the Gumbel error scale remains unidentified. Note that in our estimation the integral is approximated by simulation based on 500 quasi-random draws derived using Latin hypercube sampling (Hess, Train, and Polack 2006), and that the elements of the Cholesky matrix, rather than those of the variance-covariance matrix, are estimated. Furthermore, the effects of socioeconomic covariates can be addressed by including among the regressors mean-shifting effects using interaction variables between attributes and covariates, so that the means of the taste distribution becomes conditional on the respondents socioeconomic status z_n via a shifting parameter γ, which here is an element of $\boldsymbol{\beta}$. Welfare changes as measured by Compensating Variation (CV) from a move from $\mathbf{x}^{\circ}$ to $\mathbf{x}^1$ and conditional on individual taste $\boldsymbol{\beta}_n$ are logit and they therefore take the familiar form:

$$(5)\qquad CV_n = -(\beta_n^{\$})^{-1}\left[\ln\left[\sum \exp\left(\boldsymbol{\beta}_n'\mathbf{x}_n^1\right)\right] - \ln\left[\sum \exp\left(\boldsymbol{\beta}_n'\mathbf{x}_n^0\right)\right]\right].$$

The expected measure needs integration over taste distribution in the population:

$$(6)\qquad \widehat{CV} = \int CV_n \varphi(\hat{\bar{\boldsymbol{\beta}}}, \hat{\Omega})\, d\boldsymbol{\beta} = \int \left\{ -(\hat{\boldsymbol{\beta}}_n^{\$})^{-1}\left[\ln\left[\sum \exp\left(\hat{\boldsymbol{\beta}}_n'\mathbf{x}_n^1\right)\right] - \ln\left[\sum \exp\left(\hat{\boldsymbol{\beta}}_n'\mathbf{x}_n^0\right)\right]\right]\right\}\varphi(\hat{\bar{\boldsymbol{\beta}}}, \hat{\Omega})\, d\boldsymbol{\beta}.$$

This integral is also approximated by simulation from draws of the estimated distributions for the random parameters. However, other features of the distribution beyond the expected value can be of interest too, such as quantiles, which are less sensitive to extreme values. We note that because attributes are here subjectively rated by each kayaker rather than objectively measured, in our welfare estimation computation we use the sample average rating of each attribute $\bar{\mathbf{x}}$ to characterize the status quo perception of a representative kayaker and we do not condition these estimates upon observed choices as done elsewhere (e.g., Scarpa and Thiene 2005).

The Latent Class Model

Like the RPL, the LCM model is also a mixed logit model. The difference is that the mixing of taste intensities takes place over a finite group of k taste segments, rather than over continuous value distributions. Conditional on belonging to a taste group k with probability π_k the site-selection probability is logit. Membership probability into groups can be semiparametric and based only on a constant (Scarpa and Thiene 2005), or be informed by socioeconomic covariates (Boxall and Adamowicz 2002; Provencher, Baerenklau, and Bishop 2002). Which specification to use remains an empirical question that needs to be addressed case by case. The marginal choice probability is obtained by using the law of total probability:

$$\Pr(i) = \sum_{k=1}^{K} \pi_k L(i \mid k)$$

where $L(i \mid k)$ is the logit probability conditional on group membership, and π_k is the membership probability. For computational convenience the latter can also be specified as a multinomial logit, so as to identify a vector γ_k for each group. We note that in this case either a baseline group or some adding-up restrictions on the coefficients are necessary for identification.

In the LCM taste heterogeneity is statistically accounted for by simultaneously assigning individuals into behavioral groups or latent segments and estimating the choice model. Within each "latent" (that is, unobserved) class, preferences are assumed to be homogeneous; however, preferences and hence utility functions and welfare measures can vary between segments. A primary benefit of this approach is being able to explain the preference variation across individuals conditional on the probability of membership to a latent segment. Since in our sample of kayakers the membership probabilities are informed by attitudinal self-reported responses and are specified to be conditional on the skill of the kayaker, the formulas for class (c) membership probability can be written as

$$(7)\qquad \Pr(i \in c) = \frac{\exp(\alpha_c + \gamma_c skill_c)}{\sum_{c=1}^{c=C} \exp(\alpha_c + \gamma_c skill_c)}, \quad c = 1, 2, \ldots, C, \sum_{c=1}^{c=C} \alpha_c = 0$$

where α_c is a class-specific constant, and γ_c is the skill effect on class membership for classes 1, 2, 3, ..., C. Within the latent class structure, the probability of whitewater site i being chosen by kayaker n within the class c is exactly the same as equation (3) except that it is conditional on the class c:

$$(8)\qquad \Pr(i \mid c) = \frac{\exp(V_{in} \mid c)}{\sum_{j=1}^{J} \exp(V_{jn} \mid c)}$$

where $V_{in} \mid c = \boldsymbol{\beta}'_{cn}\mathbf{x}_{ic}$. The expected probability of whitewater site i being chosen by kayaker n is the expected value (over classes) of the class-specific probabilities. Once the parameters of the model are estimated, Greene (2003) and Scarpa and Thiene (2005) demonstrate how the individual-specific posterior class probabilities can be computed using Bayes' theorem. They show that the individual-specific posterior parameter estimates can be computed using predicted class membership probabilities $\hat{\pi}_c$ as weights of the average of the parameters over classes, $\hat{\boldsymbol{\beta}}_n = \sum_{c=1}^{C} \hat{\pi}_{cn}\hat{\boldsymbol{\beta}}_c$.

In this context, conditional on class membership, the CV is as in equation (5), while the equivalent of equation (6) is simply another weighted average:

(9)

$$\begin{aligned}\widehat{CV} &= \sum_{c=1}^{c=C} \hat{\pi}_{nc}\widehat{CV}_{nc} \\ &= \sum_{c=1}^{c=C} \hat{\pi}_{nc}\left\{-(\hat{\beta}^{m}_{nc})^{-1}\left[\ln\left[\sum \exp\left(\hat{\boldsymbol{\beta}}'_{nc}\mathbf{x}^{1}_{n}\right)\right]\right.\right. \\ &\qquad \left.\left. - \ln\left[\sum \exp\left(\hat{\beta}'_{nc}\mathbf{x}^{0}_{n}\right)\right]\right]\right\}\end{aligned}$$

where x^0_n is the status quo level of the attributes as perceived by kayaker n and x^1_n is the perceived level of the attributes after the policy change. Differently from what is implied by equation (6) these estimates do not imply a distribution of values beyond those specific for each class. Again as a baseline for the status quo we take the average attribute perception in the sample for each attribute.

Heterogeneous Preferences in Valuation Studies

There are numerous examples where RUM have been used to analyze the demand for recreational amenities (Parsons and Massey 2003; Morey et al. 2003). Many of these studies make the implicit assumption that preferences are homogenous across individuals, since a CL framework is employed. An earlier approach to account for heterogeneity was based on interactions between individual-specific variables (e.g., skill, age, etc.) with either site attributes (Adamowicz et al. 1997) or alternative-specific constants (Pollack and Wales 1992). As Boxall and Adamowicz (2002) point out, this method is conceptually limiting because, short of creating a large number of interaction variables, it requires assumptions guiding the selection of which individual covariate and choice attributes to use in the construction of interaction variables in order to distinguish the drivers of preference variation. Similar limitations are suffered by another alternative; that of specifying separate CL models for different groups of recreationists. More importantly, neither of the above methods allows the researcher to identify the probability with which patterns of taste intensity are present in the population, which instead can be captured by LCM and RPL models, albeit in different ways.

The RPL does not suffer from these limitations and hence since its first introduction in destination choice for outdoor recreation by Train (1998) it has been widely adopted (Breffle and Morey 2000; Parsons and Massey 2003). Similar success has been enjoyed by this method in other areas of applied research including transportation (Amador, Gonzales, and Ortuzar 2005), consumer choices (Revelt and Train 1998), health (Personn 2002), and waste management (Layton 2000). A second method of investigating heterogeneity within RUM is Latent Class Analysis. McFadden (1986) initiated work in this area to develop market forecasts. In an attempt to address heterogeneity of preference in a fashion that can be more promptly communicated to managers and does not involve complex estimation methods, LCM applications were also put forward (Boxall and Adamowicz 2002; Provencher, Baerenklau, and Bishop 2002; Morey, Thacher, and Breffle 2006). In another application, Birol, Karousakis, and Koundouri (2006) applied the model to preferences for wetland attributes using a choice experiment data set.

A number of studies have recently sought to compare these two approaches to modeling heterogeneity in preferences. Provencher and Bishop (2004) compare the recreation demand forecasting performance of a CL model, two RPL models; and a latent class (LC) model. No model is found to be generally superior to the others and, surprisingly, by some measures a simple CL model does better in out-of-sample forecasts than models designed to capture heterogeneity in the population. The results from this article illustrate that with heavily parameterized econometric models and a choice model that is misspecified, the addition of parameters to denote the heterogeneity of preferences will "absorb" specification errors and thus possibly generate models inferior to those of a simpler model.

Welfare estimate comparisons from RPL and LCM approaches can also be found in stated preference studies on the value of travel time (Greene and Hensher 2003) and on that of service factors to water company customers (Scarpa, Willis, and Acutt 2005). The latter paper shows that as the number of classes increases the distributions of individual-specific estimates from the LC models approximates (in shape) the distribution of an RPL model. Provencher, Baerenklau, and Bishop (2002) also compare welfare measures across LCM and RPL, but their main focus is on whether the random component of trip utility is serially correlated across trip occasions in the RPL specification. In their article, the individual-specific characteristics that influence latent class membership (age and experience) were neither found to significantly affect the means of the random variables in the RPL model they report, nor the membership probabilities in the LCM. In contrast, in our data analysis we find that individual's characteristics (i.e., self-rated kayaking skill) significantly affect both the means of the RPL random parameters and membership probabilities of the LCM. Both models capture variability of taste in a way that treats the role of individuals' characteristics in an equivalent manner. This article thus tries to take this literature forward by (*a*) undertaking a comparison of RPL and LCM approaches in a way that uses an individual's characteristics to both shift the means of the random variables in the RPL model and also to influence latent class membership in the LCM; (*b*) by focusing on the implications for welfare measures for the average sample respondent; (*c*) by examining what the two approaches show about how welfare effects are distributed across kayakers; and (*d*) in discussing which circumstances are best suited to the use of either approach. Our data set affords a considerable degree of variation in recreational site characteristics because we used *perceived* site quality measures, rather than objectively observed site quality data that inevitably induce more collinearity. We argue that perceived measures are more relevant for modeling-revealed preference data since one's perceptions of relative site qualities are what counts in driving behavior, rather than objectively determined measures. We know from other research fields that perceptions and reality may differ considerably for environmental characteristics, while it is perceived quality that more likely determines where individuals choose to visit (Adamowicz et al. 1997).

Study Design and Rationale

The initial steps in the empirical part of this study were to identify the choice sets and their relevant attributes for kayaking, in order to specify the travel cost model. To accomplish this, focus groups were conducted with kayakers from the university kayak club in Galway, and a second group consisting of seven kayakers who had no affiliations with any particular kayak club. Discussions with the Irish Canoe Union (ICU), and the experience of one of the authors with kayaking, also helped in this process. Eleven principal whitewater sites were identified and are shown in table 1 along with their grade. The site

Table 1. Whitewater Sites and Associated Whitewater Grade and Average Perceived Level of Attributes

Factor	*Grade*	Parking	Crowding	Star Rating	Water Quality	Scenic Quality	Prior Information
The Liffey	2/3	3.35	2.76	1.66	1.93	2.63	3.33
Clifden Play Hole	2	2.99	2.74	2.37	4.15	4	4.52
Curragower Wave	3	3.08	2.92	2.64	2.61	2.37	3.34
The Boyne	2/3	2.36	3.22	1.64	3.27	3.97	3.2
The Roughty	4	3.06	3.94	2.72	4.57	4.41	2.62
The Clare Glens	4/5	3.55	4.03	2.89	4.43	4.73	2.48
The Annamoe	3	3.16	2.98	2.11	4.13	4.02	3.02
The Barrow	2	2.58	3.65	2.88	4.13	4.38	2.56
The Dargle	4/5	3.88	4.13	1.32	3.43	3.68	3.13
The Inny	2	3.65	3.51	1.57	3.67	2.84	2.71
The Boluisce	2/3	2.85	3.6	2.04	4.26	3.43	2.98

Notes: The grade for each river is taken from the Irish Whitewater Guide book (MacGearailt 1996). Attributes are rated on a scale of 1 to 5, where 1 is poor and 5 is excellent. In the case of crowding 1 means very crowded and 5 means uncrowded.

attributes chosen were quality of parking at the site, degree of expected crowding at the site, quality of the kayaking experience as measured by the star rating system used in The Irish Whitewater Guidebook, water quality, scenic quality, and reliability of water information. Information was also collected on an individual's travel distance and travel time to each site. While including a "crowding" attribute introduces potential problems of regressing demand on capacity, our focus groups highlighted this as an important river characteristic in making their trip decisions.

The sampling frame was provided by two Irish kayaker e-mail lists obtained from the Outdoor Adventure Store (one of the main kayak equipment outlet stores in Ireland) and the Irish kayaking instruction company, H2O Extreme. A random sample of these e-mail addresses was selected, and questionnaires were emailed to these individuals, who were asked to complete and return the questionnaire via email. To widen the sample in terms of representativeness and increase the number of completed surveys, the questionnaire was also posted on the homepage of the Irish Canoe Union website (www.irishcanoeunion.com) and administered at an organized kayaking meet on the Liffey river in January 2004. A total of 315 surveys were send via email. The response rate to the email shot was 64%. From all collection points a sample of 279 useable responses from kayakers was acquired (202 from the e-mail shot, forty-two from the on-site survey, and the remaining thirty-five from questionnaires downloaded from the website).

The majority of respondents were male (78%). 70% of the sample was single, while 13% of those interviewed had children. The mean income before tax was €27,634. Over 44% of kayakers had been paddling for five years or less, with another 15% and 19% indicating they had been kayaking for between five and ten years and between ten and twenty years, respectively. Overall respondents had been kayaking for a minimum of 0.5 years, a maximum of thirty-six years with the mean at 7.4 years. In terms of participation, 39% of all respondents completed twenty kayaking trips or less in a year, with the next largest group completing from thirty to fifty kayaking trips in the year. Table 2 presents some further summary statistics of the respondents in the survey.

Respondents were instructed to indicate how many trips they had made to each of the eleven whitewater sites in the previous year, and were asked to rank the attributes for a site so long as they had visited that site at some point in the past. With regard to the site attributes we had to decide whether to use a subjective or an objective measure of each characteristic. Following the approach adopted by Hanley et al. (2001), each respondent was asked to rate each of the eleven sites in terms of the six attributes outlined above (using a 1 to 5 likert scale system for each attribute). The average perceived value of each attribute for each destination is shown in table 1. We assume most kayakers have, through personal experience, a good knowledge of major whitewater kayaking sites and that this allowed them to use their own judgment to rank each alternative site. These subjective ratings of attributes were used as covariates in our site choice models.

There is a potential trade-off here between possible bias (if the use of subjective measures leads to endogeneity) and a loss of efficiency (if the loss of information from moving from the individual to some sort of average or objective measure is important). The direction of the possible bias will depend on whether the respondent overestimates or underestimates the

Table 2. Summary Statistics of Respondents in Kayaking Survey

	Mean	Std. Dev.	Min.	Max.
Age in years	27.06	7.20	16	52
Education[a]	1.27	0.48	1	3
Income (€, yearly)	27,554	21,891	5,000	90,000
Importance of kayaking[b]	1.26	0.71	1	4
Travel cost (€)	55.59	37.64	1.15	274.79
Discretionary time Available(days per year)	102.88	70.71	0	365
Number of years paddling	7.22	6.27	0.5	36
Number of trips per site	3.44	14.73	0	300

[a]Education equal to 1 indicates primary school education, 2 indicates secondary-level education, and 3 indicates third-level education.
[b]Importance of kayaking as a recreational activity to the individual is measured on a Likert scale, 1–4.

true value of the quality of the site attribute. We also note that what constitutes a "higher" or "lower" level of scenic quality will vary considerably (and unobservably) across kayakers. However, a strong argument can be made that it is the perception of site qualities that drives recreational choices, so that choice models should be specified in terms of perceived attribute levels. However, policy decisions are typically set in terms of objective measures of attributes so a trade-off exists in what is more useful in terms of predicting recreationalists' behavior and the implementation of environmental policy.

Other researchers have addressed this issue. For example, Poor et al. (2001) examine the convergent validity of objective and subjective measures of water clarity for lakes in Maine using a hedonic property value study. They point out that while objective data on attributes such as water and air quality may be scientifically accurate, individual consumers are more likely to make decisions based on their subjective perceptions of these attributes, which may or may not be correlated with scientific measures. As such, Poor et al. (2005) demonstrate that the use of the scientific measures in hedonic price models may create an error-in-variables problem for the estimation of implicit prices of environmental quality. Of more relevance to the research presented in this article, Adamowicz et al. (1997) compared moose hunters' perceptions with objective measures of hunting site amenities within a random-utility model framework. Even though the objective and subjective measures of quality were not quantified using directly comparable units of measure, results indicated that the subjective measures yielded modest improvements in the predictive capabilities of their site choice models.

Rationale for Modeling Preference Heterogeneity in the Kayaking Community

Within the sport of whitewater kayaking there are a number of different specializations that can help in developing the rationale for the expected differences in preferences among kayakers of different skill and experience levels. *River running* involves the use of a paddle to negotiate one's kayak successfully through a stretch of rapids on a river. Kayakers of different proficiency levels will run rivers according to the grade of the whitewater that suits their skill level. *Freestyle* is when kayakers "park and play." They stay at the one river feature and use that feature to surf their kayaks. This area of the sport has had the most growth in the last decade. It is very skill-intensive but is considered safer than river running. Whitewater kayakers could also be categorized by the competitive aspect of the sport in which he or she is (or has been) involved. *Long distance "k-boat" kayakers* or *kayak polo enthusiasts* will enjoy rivers of lower grade. *Slalom kayakers* and *wild water racers* will favor whitewater of grade 3 or 4 and will tend to have better kayak-handling skills while *Rodeo kayakers* will probably have the highest skills and will favor park and play kayaking rather than river running. The key point is that we would expect that these different types of kayaker will place different values on the site attributes we study.

Results

In this section we present the results of the conditional logit model, which shows significant coefficients for the site-attributes interactions with kayaking skill (reported in table 3). We contrast them with the panel mixed logit models. These consist of an RPL model (RPL in tables 5 and 6) and a latent class (LCM in table 7) model. All models are estimated from our (unbalanced) panel of respondents, providing a total of data set of 3,466 kayaker site choice observations. Statistics of model performance are summarized in table 4. In all models, the dependent variable (whitewater site visit) takes a value of 1 if a kayaker has made a trip to whitewater site *i* in each of the kayaking trips taken in the previous twelve months and zero otherwise. As explanatory variables for choice probabilities we used travel cost and six site attributes; parking, crowding, star rating, water quality, scenery, and prior information on water levels. The other choice variables are constants for specific groupings of the kayaking sites.

Table 3 outlines which sites belong to which grouping. The grouping was determined by an initial specification search. In all models the excluded site dummy is the Liffey. Following the example of other researchers (see, for example, Morey, Rowe, and Watson 1993) we truncate our sample of respondents by using a ceiling of 40 trips per year to focus our analysis on those who participate in kayaking from a recreational point of view rather than a competitive one. The RPL models were estimated with BIOGEME (Bierlaire 2005) using maximum simulated likelihood (MSL)

Table 3. Conditional Logit Model, All Trips

	Coefficient	*t*-Stat
Travel cost	−0.07	−27.57*
Quality of parking	0.01	0.42
Crowding	0.02	0.57
Star quality of the whitewater site	0.22	4.52*
Water quality	−0.08	−1.96
Scenic quality	0.04	0.99
Availability of information on water levels	0.12	3.47*
Advanced skill∗Travel cost	0.03	9.20*
Advanced skill∗Quality of parking	0.05	1.11
Advanced skill∗Crowding	0.04	0.77
Advanced skill∗Star quality	0.19	2.95*
Advanced skill∗Water quality	0.16	3.84*
Advanced skill∗Scenic quality	−0.14	−2.83*
Advanced skill∗Available information on water level	0.04	0.78
River grouping 1 (Barrow, Boluisce and Clare Glens)[a]	−1.46	−16.75*
River grouping 2 (Annamoe, Roughty, Inny)[a]	−2.4	−18.98*
River grouping 3 (Boyne, Curragower Wave)[a]	−0.85	−9.37*
River grouping 4 (Dargle)	−0.7	−11.06*
River grouping 5 (Clifden Play Hole)	−0.25	−2.15*

Note: Single asterisk (*) indicates significance at 5%.
[a]Specification searches based on conditional logit models showed that individual dummies for the eleven whitewater sites showed estimated coefficients that were not statistically significant across certain sites and these were combined in a single constant for a number of sites.

estimation procedures and the CFSQP algorithm (Lawrence, Zhou, and Tits 1997), while the LCM models were estimated using Latent Gold choice (Vermunt and Magidson 2005), by using 50–100 random starting points (depending on the number of classes) and a combination of expectation-maximization (EM) and Newton algorithms to avoid the problem of local maxima. The ordinary least squares (OLS) regression of the predicted probabilities by the RPL model on a constant and the predicted probabilities by the selected LCM model has an R^2 of 82%, thereby showing that the two models have similar predictive ability.

Results from the Random Parameter Logit Model

Following an extensive specification search based on improvements on the simulated log likelihood at a maximum, we settled on the RPL model whose results are presented in tables 5 and 6. The search investigated alternative distributions for the *travel cost* parameters (e.g., uniform, S-b), interaction effects with some socioeconomic covariates as well as various specifications of the Cholesky matrix, each implying different correlation patterns in the distribution of tastes. It also investigated

Table 4. Criteria for Number of Classes

Classes	Log Lik.	BIC	AIC	crAIC	AIC3	N. Parameters
1	−6,521.6252	13,106.65	13,067.25	13,091.12	13,079.25	12
2	−6,170.1723	12,477.71	12,392.34	**12,624.96**	12,418.34	26
3	−6,036.3876	12,284.1	12,152.78	13,041.55	12,192.78	40
4	−5,948.1733	12,181.64	12,004.35	14,363.5	12,058.35	54
5	−5,889.0901	12,137.44	11,914.18	17,086.46	11,982.18	68
6	−5,845.2266	**12,123.68**	11,854.45	21,973.11	11,936.45	82
7	−5,817.4254	12,142.04	11,826.85	30,262.73	11,922.85	96
8	−5,789.5473	12,160.25	11,799.09	43,976.04	11,909.09	110
9	−5,756.3315	12,167.78	**11,760.66**	66,774.75	**11,884.66**	124
10	−5,742.5555	12,214.19	11,761.11	105,988.5	11,899.11	138
11	−5,731.1798	12,265.41	11,766.36	178,344.2	11,918.36	152
RPL	−5,984.82	12,112.29	12,023.64	12,284.64	18,035.40	27

Table 5. Random Parameters Logit Model, All Trips

	Mean		Mean
Travel Cost	−2.87	*River grouping 1*	−1.43
	(−51.67)*	(Barrow, Boluisce, and Clare Glens)	(−9.35)*
Quality of parking	0.2	*River grouping 2*	−2.31
	(3.23)*	(Annamoe, Roughty, Inny)	(−8.76)*
	3.6		
Crowding	0.1	*River grouping 3*	−0.67
	(0.83)	(Boyne, Curragower Wave)	(−0.18)
	1.83		
Star quality of the whitewater site	0.13	*River grouping 4* (Dargle)	−0.78
	(1.86)		(−6.54)*
	2.28		
Water quality	−0.13	*River grouping 5* (Clifden Play Hole)	−0.38
	(−2.11)		(−1.93)*
	−2.35		
Scenic quality	−0.01	*Water quality – Skill level interaction Dummy*	1.35
	(−0.41)		(1.95)*
	−0.25		
Availability of information on water levels prior to visiting the site	0.14	*Star quality of the whitewater site – Skill level interaction dummy*	3.21
	(2.64)*		(2.75)*
	2.45		
Attribute Covariates			
Star Quality – Crowding	0.26	*Availability of information - Water quality*	−0.08
	(2.87)*		(−1.46)
Availability of information – Crowding	0.22	*Scenic quality – Star quality*	−0.12
	(2.61)*		(−1.72)
Availability of information – Star quality	0.41	*Scenic quality – Water quality*	−0.46
	(10.02)*		(−7.51)*

Notes: Figures in parenthesis indicate t-statistics and figures in italics indicate marginal willingness-to-pay estimates for each site attribute evaluated at its mean. A single asterisk (*) indicates significance at 5%.

various interactions with socioeconomic covariates. Initial years of experience in kayaking activity were also used as a plausible variable to explain the source of heterogeneity of taste. For example, this is found to be a significant variable for class membership in LC count models of total visitation demand to the Alps by Scarpa, Thiene, and Tempesta (2007). However, the combined evidence suggests that in our data set only the level of kayaking skill significantly improves model fit and usefully informs class segregation and taste distributions. For the sake of parsimony the coefficients for site-specific group dummies are specified as fixed and so were those for the interaction variables between attributes and skill level,

Table 6. Estimates and Asymptotic z-Values for Cholesky Matrix

	Parking	*Crowding*	*Star Rating*	*Water Quality*	*Scenic*	*Information*	*ln(-TC)*
Parking	0.518						
	(11.1)						
Crowding		0.296					
		(4.5)					
Star rating		0.225	0.226				
		(3.5)	(3.3)				
Water quality				0.101			
				(1.2)			
Scenic			−0.122	−0.463	0.359		
			(−1.7)	(−8.1)	(7.8)		
Information		0.217	0.405	−0.0758		0.2	
		(4.2)	(7.6)	(−1.9)		(5.1)	
ln(-TC)							0.669
							(12.5)

which consistently showed significance. The negative of the *travel cost* coefficient was assumed lognormally distributed, while the other six site attribute coefficients were assumed to be normally distributed, so that negative as well as positive values for site attributes are permitted.[1]

The conventionally reported test of statistical significance from zero is meaningless for mean parameters if these have an associated standard deviation estimate that is significant (or another line elements of a Cholesky matrix). Together the two estimates allow an inference of what proportion of the population dislike a given attribute, and of the degree of correlation in taste attribute variation. Under normality a negative mean/median implies that a majority of people dislike the attribute. This is recorded for *Water* and *Scenic Quality*. Most people, though, like *Parking Quality, Crowding, Star rating,* and *Availability of Information*. Since eleven of the twenty-one elements of the Cholesky matrix presented in table 6 are significant at the 5% level, this supports the existence of a correlation structure across varying taste intensities. Note that this is true even though we allow for the means of the random parameters on our site attributes to depend on a personal characteristic (self-reported skill). This echoes results from Revelt and Train (1998) and Scarpa, Philippidis, and Spalatro (2005), who found that significant unobserved heterogeneity still remained even after including several demographic variables in interactions with choice attributes. This result is consistent with the fact that preferences vary considerably more than can be explained by observed characteristics of people. The whitewater group dummies are all significant and all sites display a negative sign indicating that the reference site has a higher share of visits.

Results from the Latent Class Model

With respect to the definition and testing of hypothesis on the number of classes in the latent class model the conventional specification tests used for maximum likelihood estimates (likelihood ratio, Lagrange multipliers, and Wald tests) are not valid as they do not satisfy the regularity conditions for a limiting chi-square distribution under the null. Therefore, in order to decide the number of classes with different preferences, we use an information criteria statistic developed by Hurvich and Tsai (1989). The information criteria statistic (C) is specified as $-2\ln L + J\delta$ where $\ln L$ is the log likelihood of the model at convergence, J is the number of estimated parameters in the model, and δ is a penalty constant.

There are a number of different types of information criteria statistics that can be employed. Each one depends on the value taken by the penalty constant δ. For $\delta = 3$ we obtain the Akaike Information Criteria (AIC); for $\delta = \ln(N)$ we obtain the Bayesian Information Criteria (BIC) and finally, for $\delta = 2 + 2(J+1)(J+2)/(N-J-2)$ we have the corrected AIC (crAIC), which increases the penalty for the number of extra parameters estimated. Even though these criteria statistics are very useful in deciding on what the optimum number of classes is, they have been shown to fail some of the regularity conditions for a valid test under the null (Leroux, 1992). In a recent Monte Carlo study Andrews and Currim (2003) concluded that the AIC 3 (the AIC with a penalty factor of 3) was the best segment-retention criterion to use across a large variety of multinomial data configurations. They did, however, indicate that it is unrealistic to assume that one segment-retention criterion is best for mixtures of all types of distributions in all situations. For this reason we examine three alternative information criteria statistics.

The values for the selected information criteria of different preference groups are reported in table 4. The BIC statistic indicates that there are six classes with satisfactory parameter estimates. Having said this, the crAIC would indicate two classes with satisfactory parameter estimates, while the AIC and the AIC3 indicate as many as nine. The information criteria provide guidance on the number of latent classes to choose (Thacher, Morey, and Craighead 2005). As Scarpa and Thiene (2005) point out, however, this decision also requires the discretion of the researcher. In particular,

[1] When specifying some of the coefficients, such as scenery and water quality, to follow a lognormal distribution, we failed to get the model to converge. Following Brownstone and Train's (1999) example we explored the use of lognormal distributions to circumvent this problem. However, the model still failed to converge. Therefore, our model treats all noncost coefficients as random and normally distributed. Restrictions in the choice of distributions are stronger when using maximum simulated likelihood because of its reliance on gradient methods to find the maximum (Rigby and Burton 2005; Train and Sonnier 2005), but more choice exists when using hierarchical Bayes estimation (Sillano and Ortuzar 2005) in which convergence is determined on the basis of the stability of posterior draws. Added flexibility (e.g., multimodal distributions) can be obtained by using semi-nonparametric approaches based on polynomials (Fosgerau and Bierlaire 2007; Scarpa, Thiene, and Marangon 2008).

they state that "the chosen number of classes must also account for significance of parameter estimates and be tempered by the analyst's own judgment on the meaningfulness of the parameter signs." We hence choose only to report the LCM estimate for six classes, as the two-class model mostly showed insignificant attribute coefficients, while nine classes are simply too numerous. The indirect utilities for class 4 and 5 also have a high number of insignificant parameter estimates.

The basic specification of the LCM model is the same as that of the RPL model. We specify our latent classes as a function of the kayak-handling skill of the kayaker (skill takes the value zero if the kayaker has basic or intermediate kayak-handling skills and one if he or she has advanced kayak-handling skills). The results of the latent class model with six class segments are presented in table 7. For each site attribute we report coefficient estimate, asymptotic z-value, and marginal WTP. The latter facilitates comparisons across classes since direct comparison of coefficient values is not very meaningful. Classes are ordered on the basis of their share in the sample, which varies from 34% (class 1) to 4% (class 6). *Travel costs* coefficients are negative and significant in all classes, while quality of information is significant in none, so classes are mostly characterized by the variation of intensity and significance of estimates for coefficients of other attributes.

Star quality and *scenic quality* tend to be significant in smaller share classes. Kayakers in class 1, with the largest share, seem to be significantly driven in site selection only by the amount of *crowding*, while those in class 2 only by *quality of information* and *star quality*. This last feature—instead—is strongly disliked by kayakers in class 3 (share of 16%), who also dislike *scenic quality*. Selection of sites for members in class 4 (share of 14%) is positively driven by *quality of parking* and *star quality*, but negatively driven by *crowding* and *scenic quality*. Class 5 and 6 account for less than 12% of shares and we omit a discussion of their preferences here. *Water quality* does not seem to be very relevant in site selection. This is not surprising as kayakers do not generally take much notice of the quality of the water unless the pollution levels are extreme. Indeed, the most frequented white water site in our sample was the "Sluice" whitewater site on the river Liffey, which is the most polluted of the whitewater sites considered in this analysis.

For our six-class model of table 7, we would speculate that class 5 is representative of the basic- or intermediate-skilled *river running* kayaker, favoring higher star rated runs, uncrowded rivers, and good parking facilities. The probability of any kayaker in our sample being described by this class is low at only 0.07. Class 6 kayakers could be thought of as the more advanced-skilled, *river running* kayakers. From the estimated coefficients it can be seen this group also prefer higher star quality runs, uncrowded rivers, and good parking facilities. They also prefer more scenic whitewater sites. These individuals have more experience and skill so they can afford to take in the beauty of the scenery around them rather than focusing completely on getting down the river in one piece as may be the case for the less experienced river runner described by class 5 (scenic quality coefficient has a negative sign for class 5).

Class 3 kayakers could be thought of as *competitive, long distance "k-boat" racing* kayakers. From the estimated coefficients it can be seen this group would appear to be unconcerned about the water quality, parking, or prior information on water levels attributes of the river. They prefer lower star rated runs that are less scenic. Basically, they simply require a venue to train and race. Class 4 kayakers could be thought of as the *freestyle or playboating* kayakers with more advanced kayak-handling skills. From the estimated coefficients it can be seen that this group prefer good parking facilities but prefer having more people on the water with them (negative sign on the crowding coefficient), perhaps to show their freestyle moves off to. They are positively concerned about water quality (since they are likely to be in (and under) more turbulent whitewater, polluted water could have much more serious health consequences). The star rating of the site also appears to be important (significant) for this group, which is what one would expect.

We would speculate that class 1 represents the less-skilled *freestyle playboaters*. As can be seen from the signs on the coefficients these kayakers prefer (as we would expect) better parking facilities, proper prior information on water levels, and uncrowded playspots. Judging by the negative sign on the *star rating* coefficient and positive and significant sign on the *crowding* variable this group also prefers easier features to learn their freestyle moves where fewer people are present to get in their way. Finally, class 2 kayakers could be thought

Table 7. Latent Class Model, Six Classes

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Travel cost	−0.12	−0.06	−0.01	−0.03	−0.13	−0.07
	(−19.9)*	(−14.2)*	(−4.8)*	(−5.0)*	(−6.7)*	(−5.8)*
	0.15	−0.11	0.06	0.19	0.59	2.15
Quality of parking	(1.6)	(−1.6)	(1.2)	(1.8)*	(3.9)*	(7.0)*
	1.25	*−1.83*	*6.00*	*6.33*	*4.54*	*30.71*
	0.23	−0.09	−0.05	−0.14	1.61	0.91
Crowding	(3.0)*	(−1.4)	(−1.0)	(−2.6)*	(10.3)*	(2.2)*
	1.92	*−1.50*	*−5.00*	*−4.67*	*12.38*	*13.00*
	−0.02	0.65	−0.34	0.4	2.02	2.2
Star quality of the whitewater site	(−0.1)	(3.6)*	(−3.9)*	(4.9)*	(4.6)*	(4.5)*
	−0.17	*10.83*	*−34.00*	*13.33*	*15.54*	*31.43*
	−0.13	0.02	0	0.04	−0.44	0.52
Water quality	(−1.1)	(0.2)	(0)	(0.5)	(−2.3)*	(1.4)
	−1.08	*0.33*	*0.00*	*1.33*	*−3.38*	*7.43*
	−0.15	0.08	−0.11	−0.32	−0.37	0.51
Scenic quality	(−1.6)	(1)	(−2.0)*	(−2.8)*	(−2.3)*	(2.3)*
	−1.25	*1.33*	*−11.00*	*−10.67*	*−2.85*	*7.29*
Availability of information on water	−0.06	0.13	−0.05	0.02	−0.06	0.33
levels prior to visiting the site	(−0.7)	(1.9)*	(−0.8)	(0.4)	(−0.3)	(1.2)
	−0.50	*2.17*	*−5.00*	*0.67*	*−0.46*	*4.71*
River grouping 1	−1.56	−1.52	−1.53	−0.38	0.83	−8.59
(Barrow, Boluisce, and Clare Glens)	(−5.3)*	(−5.3)*	(−10.6)*	(−1.5)	(1.5)	(−9.4)*
River grouping 2	−10.33	−2.79	−0.19	−1.92	−3	−9.31
(Annamoe, Roughty, Inny)	(−17.3)*	(−9.7)*	(−0.8)	(−4.0)*	(−2.2)*	(−10.5)*
River grouping 3	−1.3	−0.95	0.04	−0.54	−1.16	−5.31
(Boyne, Curragower Wave)	(−4.3)*	(−4.3)*	(0.2)	(−1.5)	(−1.6)	(−7.3)*
River grouping 4 (Dargle)	−0.85	−0.56	−0.61	−0.82	0.85	−3.96
	(−4.6)*	(−3.5)*	(−3.9)*	(−3.0)*	(2.3)*	(−6.2)*
River grouping 5 (Clifden Play Hole)	0.44	−0.68	−0.57	0.58	7.12	−3.78
	(1.1)	(−2.2)*	(−2.3)*	(1.9)	(6.2)*	(−3.2)*
Class probability						
Constant	1.59	0.42	−0.64	0.11	0.11	−1.59
	(6.2)*	(1.2)	(−1.4)	(0.3)	(0.3)	(−1.8)*
Kayak-handling skill	−1.35	1.3	2.07	0.71	−4.18	1.45
	(−2.9)*	(3.1)*	(4.1)*	(1.5)	(−9.2)*	(1.5)
Mean posterior probability estimates	0.34	0.26	0.16	0.14	0.07	0.04
Log likelihood			−5,845.23			

Notes: Figures in parenthesis indicate z-statistics and a single asterisk (*) indicates significance at 5%. Figures in italics indicate marginal willingness-to-pay estimates for each site attribute evaluated at its mean.

of as the competitive *rodeo kayaker* or competitive *wild water or slalom* kayakers. The *star rating* of the river or play spot is the only significant concern of these individuals. This group of kayakers could be considered perhaps the highest skilled of any of the classes and would be described by their kayaking peers as "extreme" playboaters or river runners.

The individual-specific posterior class probabilities were calculated as outlined in section 3. The average values for class segments 1, 2, 3, 4, 5, and 6 were found to be 0.34, 0.26, 0.16, 0.13, 0.06, and 0.03, respectively. We use the individual-specific posterior class probabilities in the next section, where the estimated results from the RPL model and the latent class model will be used to look at the welfare impacts of a number of whitewater site changes.

Welfare Impacts of Site Changes

Estimating the welfare effects of changes in the quality or supply of environmental goods is the main objective of most environmental valuation studies. In this section, we therefore consider the implications for welfare measures of the choice between latent class and random parameter approaches, for a number of policy scenarios. These include (*a*) a €3 parking

Table 8. Welfare Change from Policy Scenarios Per Kayaker Per Choice Occasion from RPL Model

RPL Quantiles	€3 Parking Fee at Liffey			Perceived Water Quality Improvement at Liffey			Perceived Star Rating Increase for the Barrow		
	Representative	Skilled	Unskilled	Representative	Skilled	Unskilled	Representative	Skilled	Unskilled
0.025	−1	−1.05	−0.91	−3.11	−2.71	−3.81	−0.4	−0.35	−0.45
0.05	−0.87	−0.92	−0.79	−2.22	−1.9	−2.75	−0.29	−0.25	−0.32
0.1	−0.74	−0.78	−0.66	−1.39	−1.19	−1.69	−0.18	−0.16	−0.2
0.5	−0.34	−0.35	−0.31	0.75	0.65	0.9	0.12	0.11	0.13
0.9	−0.13	−0.13	−0.12	6.56	5.84	7.62	1.97	1.76	2.16
0.95	−0.09	−0.09	−0.09	9.72	8.7	11.3	3.4	3	3.72
0.975	−0.07	−0.07	−0.07	13.45	12.11	15.59	4.92	4.34	5.35
Mean	−0.39	−0.41	−0.36	1.89	1.7	2.2	0.67	0.59	0.73

Source: Calculated from model results reported in table 5 and based on 10,000 draws from the estimated population distribution.

fee being introduced at the put-in to the Liffey river, (*b*) a policy aimed at increasing by one unit, the perception of water quality also at the river Liffey, and finally (*c*) a policy aimed at increasing by one unit the perception of star quality at the river Barrow. The welfare results based on the CL model of table 3 yield welfare estimates for the representative kayaker of −1.36, 0.34 and 3.15 for each scenario, respectively.

The welfare results based on the RPL and the LCM are shown in tables 8 and 9 and all results are based on the tastes of a representative kayaker (the average perceived attribute ratings in the sample) and refer to a trip selection occasion. We also report estimates for skilled and unskilled kayakers, since this variable was found to be associated with heterogeneity of tastes, and the two conditions are mutually exclusive. The RPL provides a distribution of Consumer Surplus (CS) values, which we have simulated with 10,000 normal draws computing equation (5) and ordering the results to identify percentiles. The average values of these are used as an approximation to equation (6). Introducing an access fee to Liffey produces a median loss of €0.34, with a mean of €0.39. Skilled kayakers suffer a bit more than unskilled ones. Increasing by one unit the water quality rating at the Liffey produces a loss for some and a gain for others. Gains exceed losses as the simulated mean is €1.89 per choice occasion, and the mean gain is slightly smaller for skilled (€1.70) than for unskilled (€2.20) kayakers. Increasing the perceived star rating for the representative kayaker for the river Barrow gives a distribution with much smaller variance and a mean value of €0.67 per choice occasion. For the skilled representative kayaker the mean value is slightly smaller (€0.59) than for the unskilled one (€0.73).

Table 8 reports the equivalent distribution of CS estimates for the LCM model. These vary across class, with each class having a specific CS estimate. For the access fee at the Liffey the overall (weighted) mean across classes for the representative and the skilled kayaker is very similar to the mean of the distribution obtained by RPL, but it is higher by a factor of over four

Table 9. Welfare Change from Policy Scenarios Per Kayaker Per Choice Occasion from LCM Model

Class (Share)	€3 Parking Fee at Liffey	Perceived Water Quality Improvement at Liffey	Perceived Star Rating Increase for the Barrow
Class 1 (0.34)	−0.30 (0.21)	−0.45 (0.24)	−0.24 (0.12)
Class 2 (0.26)	−0.54 (0.32)	0.05 (0.08)	0.03 (0.01)
Class 3 (0.16)	−3.13 (0.18)	−0.03 (0.02)	−0.01 (0.01)
Class 4 (0.14)	−1.28 (0.12)	0.27 (0.14)	0.14 (0.04)
Class 5 (0.07)	−0.27 (0.22)	−0.03 (0.04)	−0.02 (0.03)
Class 6 (0.04)	−0.51 (0.25)	5.29 (2.30)	2.66 (1.80)
Representative kayaker	−0.33 (0.12)	1.19 (0.42)	0.6 (0.22)
Representative skilled	−0.36 (0.18)	1.22 (0.38)	0.61 (0.24)
Representative unskilled	−1.61 (0.28)	1.17 (0.42)	0.59 (0.34)

Source: Calculated from model results reported in table 7 (Krinsky-Robb approximation to standard errors in parentheses).

for the unskilled kayaker. For changes in water quality perception at the Liffey we notice that RPL estimates are about one-third higher than the LCM ones, but the discrepancy is within sampling variation. The LCM estimates for a star rating increase at the Barrow are remarkably similar to those obtained by RPL.

Conclusions

This article examined alternative ways of modeling heterogeneity of tastes for an outdoor recreational good. We contrasted two modeling techniques, namely, the random parameter logit model and the latent class model and used them to explain whitewater site choice in Ireland. We then derived welfare estimates relating to three policy scenarios relating to perceived changes in the quality of the kayaking experience at two of the whitewater sites. The distribution of these welfare estimates were derived conditional on factors that determine taste changes among kayakers; in our case, skill level. What this article contributes to the literature is a comparison of two models on data based on perceived, rather than measured attributes, where the individual-specific characteristic of skill level is allowed to both shift the means of the random variables in the RPL model and to influence latent class membership in the LCM.

Given the relatively small sample size and the method by which our sample was self-selected (in particular the 77 respondents who either downloaded the questionnaire from the website or took part in the on-site portion of survey) it would be wise to take a cautious view as to how representative these results are of the population of Irish kayakers. The results presented in the article, therefore, must be viewed as conditional upon the, in part, self-selected sample.

There was considerable difference in the value of the welfare estimates across the skill levels within both the RPL and latent class models. The RPL model implies that skilled kayakers on average experience larger welfare impacts from all of the policy scenarios considered compared to their unskilled counterparts. This finding does not hold true for the latent class model. In this case the mean gain for both the perceived increase in water quality at the Liffey and the perceived increase in the star rating at the river Barrow is slightly larger for unskilled than for skilled kayakers. Overall however, the estimated welfare impacts of the investigated policy scenarios for the representative kayaker are remarkably similar between the two approaches. So does choice of method for incorporating preference heterogeneity actually matter? And how can we judge which approach to modeling unobserved preference heterogeneity is preferable?

Provencher and Moore (2006) have argued that this choice should depend on what one believes about underlying preferences. If they are really unique to individuals (they use the idea of a fingerprint), then the RPL approach makes more sense. The RPL method also identifies which attributes have significant levels of heterogeneity in preferences, and quantifies the degree of the spread of values around the mean. However, the analyst must impose a distributional form on preferences, and welfare estimates are known to be quite sensitive to this choice. Moreover, allowing for a full pattern of correlation between preference parameters can be difficult, since this entails the estimation of $(k^2-k)/2$ additional parameters with k varying parameters.

If we think, on the other hand, that the spread of preferences is "lumpy," such that broad classes of people exist with rather similar values to each other, but rather different values to everyone else, then the latent class approach makes more sense. Preferences can now move together between groups, so that the "problem" of preference correlation is, in a sense, endogenized. In our latent class analysis we presented evidence in favor of the existence of six distinct preference groups, partly explained by skill levels, and we were able to provide an intuitive explanation for what types of kayakers populate each group. The latent class approach also generates additional information that is potentially very useful to recreational site managers, simply by identifying groups of like-minded users with particular demands (Morey, Thacher, and Breffle 2006). For example, knowing that *freestyle kayakers* are likely to be the only group found at a site such as Clifden allows us to concentrate on the parameter estimates of class 1 and 4 in our LC model when appraising maintenance or improvement plans for this whitewater destination.

In terms of future research, it would be interesting to compare the coefficient results of the models presented, which are based on respondents' subjective ratings of the whitewater site attributes, to the coefficients from models where the attribute measures are exogenously specified by the researcher—although this would be difficult for attributes such as landscape quality. It would also be interesting to see by how much the corresponding welfare estimates deviate. Another area for future research would be to compare the results of the continuous mixed logit model (the LC model) employed in this article to the mass-point mixed logit model. Compared to the continuous mixed model, the mass-point mixed model reduces computational time significantly and is free from simulation biases as it has a closed form formulation (Dong and Koppelman 2003). It also relaxes the need to make a priori assumptions on the distribution of parameters. It would be interesting to test if relaxing this distribution assumption (to a mass-point distribution) might result in too simple a representation for the complicated taste variations across the kayaking population.

Randall (1997) foresaw the changes in nonmarket valuation research methodologies when he said "the future belongs to a broad-based research program of learning about preferences from what people tell us, whatever it takes." This article has compared two possible methodologies that attempt to implement Randall aspirations. We would argue that the latent class method has an advantage over the RPL approach even though in this case few differences emerge empirically in the welfare estimates, in its powerful combination of being able to specify a model that simultaneously estimates the marginal benefits associated with different attributes for different groups, and assigning group membership. We believe that the LCM approach may offer a much more in-depth understanding of the heterogeneity of recreational preferences than the RPL model. The latent class model, put simply, provides a greater range of potentially useful information for natural resource managers.

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