Analysing Preference Heterogeneity using Random Parameter Logit and Latent Class Modelling Techniques

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Abstract

Multi-attribute revealed preference data is used to investigate the heterogeneity of tastes in a sample of kayakers, in relation to eleven whitewater sites in Ireland. The paper focuses on a comparison of the analysis of preference heterogeneity using a random parameter logit model and a latent class model. We assess and contrast the evidence for the presence of a finite number of 2, 3, 4 and 5 latent preference groups (classes), and contrast these with the presence of a continuous distribution of parameter estimates using the random parameter logit model. Welfare estimates associated with changes in the attributes of particular whitewater sites are also presented, and are found to vary considerably depending on the approach taken..

Keywords: Whitewater kayaking, random parameter logit, latent class models, preference heterogeneity.

JEL Classification: Q51 Q56

1. Introduction

The assumption that preferences are homogenous has traditionally been a “given” in revealed preference analysis of non-market goods. However, as Train (2003) points out, explicitly recognising the presence of heterogeneity in preferences is of importance in the estimation of random utility models, since otherwise biased attribute coefficient estimates result, leading to misleading welfare measurements of changes in site attributes, and hindering the proper aggregation of welfare measurements across individuals. This can adversely affect policy decisions by skewing the welfare distribution of decisions regarding natural resource management. The object of the paper is to discuss and compare two different methods of incorporating preference heterogeneity into discrete-choice recreational demand modelling, making use of a revealed preference data set of whitewater kayakers in Ireland.

In this paper, we compare two empirical models used to take account of individual heterogeneity in analyzing whitewater kayaking site choice decisions. The two models are the random parameter logit model and the multinomial logit latent class model (LCM). The Random Parameters Logit (RPL) model and LCM are chosen because they are regarded by many researchers as the most promising discrete choice analytical models available, and represent fundamentally different approaches to modeling heterogeneity than that employed in more traditional fixed parameter logit models, such as exogenously-imposed divisions of the sample (Greene and Hensher, 2002).

Kayakers’ appreciation of a kayaking site is determined by a possibly large number of site and route features, such as its grade or star rating, the scenic quality of the whitewater site, and the degree of crowding on the water (Hynes et al., 2005). As such, 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 Ireland in deciding on where to go on a particular kayaking trip. Also, we would expect to find that preferences for different types of whitewater site attributes would be affected by the kayaking skill level and the years of experience that the kayaker. The results of our two models that incorporate kayaker heterogeneity into the whitewater site choice analysis indeed appear to indicate that kayaker preferences for recreational demand sites are likely to be characterized by systematic heterogeneity. Which approach is taken to model this heterogeneity turns out to have a big impact on welfare estimates of site quality or access changes.

In the next section we review previous valuation research on water-based recreational activities that focus on issues of heterogeneous preferences. In section 3 we discuss the two multinomial based modeling approaches that may be used to analyse multi-attribute products such as whitewater kayaking site choice demand, while at the same time take into account kayaker heterogeneity. Section 4 then describes the design of our survey and summarises some sample characteristics. Model results are presented in section 5 while estimates of consumer surplus from whitewater recreation on Irish rivers, as predicted by our alternative models, are presented in section 6. Finally, section 7 concludes with some recommendations for further research.

2. Heterogeneous Preferences in Water Based Recreational Studies

There are numerous examples where the Random Utility (RUM) model has been used to analyse the demand for water based recreational amenities; (McConnell and Strand, 1994) for Atlantic sports fishing, (Parsons and Massey, 2003) for beach recreation, (Hynes et al., 2005) for kayaking and (Sidererlis et al., 1995) for boating. All of these studies, however, make the assumption that preferences are homogenous across individuals. An early solution to this problem was to interact specific individual variables, such as income or race with various choice attributes (Adamowicz et al., 1997), or with alternative specific constants. In this manner, heterogeneity was introduced into the basic RUM framework. Pollack and Wales (1992) summarize this method of using demand parameters interacted with demographic variables. However, as Boxall and Adamowicz (2002) point out, this method is limited in practice because it requires prior knowledge regarding which individual and choice variables to interact in order to distinguish groups with similar preferences. A similar information requirement is involved with another alternative: that of specifying separate MNL models for different groups of recreationalists. For instance, Hanley et al. (2001) estimate separate MNL models for summer and winter rock-climbers in Scotland. However, no objective means exist for knowing whether the sub-divisions imposed by the researcher are the most appropriate given the (unknown) variability in tastes of the sample of recreationalists.

An alternative modelling approach to the basic RUM that allows preferences to vary across respondents with equivalent characteristics is Train's (1998) Random Parameter Logit (RPL) approach, which we set out in detail below. Examples for water based recreation include studies on Atlantic salmon fishing (Morey et al., 2005), fishing site choice in Montana (Train, 1998) and participation and site choice in the Wisconsin Great Lakes region (Parsons and Massey, 2003). Both the Train (1998) and Phaneuf et al. (1998) studies find that randomizing parameters significantly improves model fit and significantly affects consumer surplus estimates for changes in environmental quality. RPL has also been applied to choice experiments to model demand for a wide array of environmental amenities other than water based ones. These include rock climbing (Hanley et al, 2003) and eco-tourism development (Hearne and Salinas, 2002).

Another literature investigating heterogeneity that has emerged in the field of recreation demand discrete-choice modeling in the last decade is latent constructs based on individual attitudes and perceptions. McFadden (1986) initiated work in this area to develop market forecasts. Ben-Akiva *et al.* (1997), Provencher et al. (2002) and Boxall and Adamowicz (2002) are some of the first applications of latent-class models in environmental economics. Provencher et al. (2002) is a latent-class model of site-choice estimated with choice experiment data. The Boxall and Adamowicz (2002) latent-class model is estimated with both attitudinal and choice data. Their model assumes that the probability that an individual belongs to latent class c is a function of his or her answers to attitudinal questions posed as part of their survey. This is very similar to the strategy adopted here. Their analysis supported the existence of four classes with homogeneous preferences, and consequently affords a much richer interpretation than a conventional multinomial logit model.

A more recent application of the Latent class (LC) model in a water based recreation setting is Morey et al. (2005) for preferences over fishing characteristics at Green Bay, Wisconsin. They employ an Expectation-Maximization estimator on responses to Likert-scaled attitudinal questions to segregate a sample of Great Lakes anglers into two to four attitudinal classes. They once more show how membership probabilities obtained using the latent class modeling techniques can be used to estimate structural random utility models. They also compare results to that of the basic multinomial logit model. Finally, Provencher and Bishop (2002) model anglers' decisions of recreation participation and evaluate the models' performance on the basis of out-of-sample forecast accuracy. They find similar results are produced from random parameter and latent class logit specifications.

Our study adds to this literature; (i) by being the first, to the best of our knowledge, to compare RPL and latent class analyses using a revealed preference data set; (ii) by using the skill level and years of experience of recreationalists to split a sample into alternative classes and thereby model the heterogeneity in the recreationalist population and (iii) by being the first study to utilise the RPL and the LC Model to analyse any outdoor recreation pursuit in Ireland and also the first application of these particular models to the sport of whitewater kayaking. In addition, we use our models to produce estimates of welfare change that are of potential relevance to any policy-making that has an impact on whitewater kayaking sites in Ireland. In the next section we set out the two multinomial based modeling approaches that we use to analyse the heterogeneity of preferences within the Irish kayaking population for whitewater kayaking sites.

3. Methodology

The random utility model (RUM) of McFadden (1974) is the standard statistical economic model used to estimate recreation choice (in a setting such as ours, this is characterized by kayaker choice between several whitewater sites with varying attributes). Its first recreational choice application was Bockstael et al. (1987). The main idea of the RUM model is that the individual chooses from a number of alternatives (e.g. whitewater sites) and picks the one that yields the highest utility level on any given choice occasion. Assume that a kayaker, *i*, has J possible multi-attribute whitewater sites from which to choose. The basic choice model for our kayaker is then given by:

$$U_{ij} = V(X_{ij}, y_i - p_{ij}) + \varepsilon_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

U_{ij} is the indirect utility of kayaker i from visiting whitewater site j. $V(.)$ is the deterministic part of the indirect utility function and ε_{ij} is the stochastic part. X_{ij} is a vector of site attributes, y is income and p_{ij} is travel cost. Whenever the utility from visiting site *j* is greater than the utility from visiting all other sites J, site *j* will be chosen, i.e. if

$$V(X_{ij}, y - p_{ij}) + \varepsilon_{ij} \geq V(X_{iJ}, y - p_{iJ}) + \varepsilon_{iJ} \quad \forall J \tag{2}$$

then site *j* will be chosen. 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 multinomial (conditional) logit (McFadden, 1974). This implies that the probability of choosing site *j* is given by:

$$pr_{ij} = \frac{\exp(V_{ij})}{\sum_{k=1}^{J} \exp(V_{ij})} \tag{3}$$

where pr_{ij} is the probability that site *j* is chosen. The conditional logit model is restricted by the independence of irrelevant alternatives (IIA) assumption (Luce, 1959) IIA assumes that the ratio of probabilities of choosing any set of alternatives remains constant no matter what happens in the remainder of the choice set. The IIA assumption implies that the errors in estimating utility across alternatives are un-correlated.

3.1 The random parameter logit model

The Random Parameter logit model generalizes the multinomial logit model by allowing the coefficients of observed variables to vary randomly over people rather than being fixed. By partitioning the stochastic component (ε_i) of equation (1), into two additive (i.e. uncorrelated) parts we allow for the possibility that the information relevant to making a choice that is unobserved may indeed be sufficiently rich in reality to induce correlation across the alternatives in each whitewater choice situations. One part is correlated over alternatives and heteroskedastic, and another part is independently, identically distributed over alternatives and individuals as shown in equation (4)

$$U_{ij} = b' X_{ij} + \eta' X_{ij} + \varepsilon_{ij} \qquad (4)$$

where b' is a vector of coefficients that is unobserved for each kayaker and varies randomly over kayakers representing each individuals tastes, and ε_{ij} is once again the unobserved random term that is independent of the other terms in the equation, and is identically and independently distributed. This specification is the same as for the condition logit, except that now the coefficients of V_{ij} vary in the population rather than being fixed. The variance in V_{ij} induces correlation in utility over sites and trips. In particular, the coefficient vector for each kayaker can be expressed as the sum of the population mean, b, and individual deviation, η' which represents the kayakers tastes relative to the average tastes in the population of all kayakers.

As Train (1997) points out, the researcher estimates b but does not observe η' for each kayaker. The unobserved portion of utility is therefore $\eta' X_{ij} + \varepsilon_{ij}$. This term is correlated over sites due to the common influence of η', i.e. the kayaker evaluates each site using the same tastes. Because the unobserved portion of utility is correlated over sites, RPL does not exhibit the independence from irrelevant alternatives property of standard conditional logit. In order to estimate this model it is necessary to make an assumption over how the coefficients *b* are distributed over the population of kayakers. Train (1997) assumes them to be distributed either normally or log-normally.

3.2 The multinomial logit latent class model

Heterogeneity can also be statistically accounted for by utilizing the latent class logit (LC) approach or finite mixture model (suggested in a RUM setting by McFadden (1986), and later developed by Swait (1994) and Boxall and Adamowicz (2002)). This is achieved by simultaneously assigning individuals into behavioural groups or latent segments, and estimating the choice model (Hyde, 2004). LC analysis was actually first introduced in 1950 by Lazarsfeld (1950), who used the technique as a tool for building typologies (or clustering) based on dichotomous observed variables. It is only in the last decade that one can find applications of the model in the non-market valuation setting. Examples include Boxall and Adamowicz (2002), Provencher et al. (2002) and Provencher and Bishop (2004)

Within each latent class, preferences are assumed to be homogeneous; however preferences and hence utility functions, 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. The basic idea underlying latent class (LC) analysis is a very simple one; some of the parameters of a postulated statistical model differ across unobserved subgroups. These subgroups form the categories of a categorical latent variable (Vermunt and Magidson, 2003). The application here identifies and characterizes two discrete, latent preference classes of kayakers that differ in their attitudes towards recreational kayaking characteristics of whitewater recreation sites in Ireland (see table 1). These characteristics include the quality of parking, crowding, water and scenery at the whitewater site, as well as travel cost, star rating of the whitewater and reliability of information on water levels.

Within the latent class structure, the probability of whitewater site *j* being chosen by kayaker *i* within the class *c* is exactly the same as equation (3) except that it is conditional on the class *c*.

$$\Pr ob(class = c) = \Pr_{icj} = \frac{\exp(V_{ij})}{\sum_{j=1}^{J} \exp(V_{ij})} \quad (6)$$

where $V_{ij} = b_c ' X_{icj}$. The expected probability of whitewater choice j being chosen for kayaker i is the expected value (over classes) of the class specific probabilities, that is:

$$P_{ic} = \sum_{c=1}^{C} \Pr ob(class = c) \left[\frac{\exp(V_{ij})}{\sum_{j=1}^{J} \exp(V_{ij})} \right] \quad (7)$$

Once the parameters of the model are estimated, both Roeder et al. (1999) and Greene (2003) 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 as the weighted average of the parameters over classes, $\hat{B}_i = \sum_{c=1}^{C} \hat{P}_{ic} \hat{B}_c$.

In this paper, we shall compare these three separate (but related) choice models in terms of the Hicksian welfare measures that they imply. The Hicksian welfare measure (as measured by compensation variation (CV)) for a change in a choice attribute (in our case improved quality of a characteristic at a whitewater kayaking site) based on a standard conditional logit model is the log-sum formula (Hanemann, 1984):

$$CV_i = -1/\beta_m \left[\ln\left[\sum \exp(V_i^1(b_i^1))\right] - \ln\left[\sum \exp(V_i^0(b_i^0))\right] \right] \quad (8)$$

The expression in (8) is also the key to computing the welfare measures in our other two empirical models as well. In the random parameter logit model, some of the $\beta's$ are random. By integrating the formula in (8) with respect to these random $\beta's$, the expected welfare gain (or loss) associated with a change in a whitewater site attribute can be derived ($\int CV(\beta)d\beta$). A simulation approach of random draws from the estimated distribution of _s is employed to compute the multiple integrals (Train, 1998). In the case of the latent class model, the $\beta's$ will differ across classes. The expected welfare gain (or loss) associated with a change in a whitewater site attribute, based on the latent class model, can be estimated by calculating the weighted sum of welfare measure in all classes, weighted by the posterior individual specific class probabilities (Boxall and Adamowicz, 2002):

$$CV_i = \sum_{c=1}^{C} P_{ic}[-1/\beta_m \left[\ln\left[\sum \exp(V_i^1(b_i^1))\right] - \ln\left[\sum \exp(V_i^0(b_i^0))\right]\right] \qquad (9)$$

In regards to the latent class model, if resource managers are interested in aggregate welfare measures over the sample, these can be calculated by (9). Hilger (2003) notes that this welfare measurement is an improvement over the traditional welfare calculation using coefficient estimates from the standard conditional logit model due to the proper weighting of each class's compensating variation. Welfare measurements for an arbitrary change in one or more of the attributes can also be calculated for each latent segment separately by simply using formulae (8) for each segment.

4. Study Design and Rationale for modelling preference heterogeneity

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 7 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 (Hynes) with kayaking, also helped in this process. Eleven principal whitewater sites were identified, and are shown in Table

3. With regards to site attributes, we chose to use respondents' perceived or subjective measures for all attributes other than travel cost, following the procedure set out in Hanley et al. (2001). We assume most kayakers have, through personal experience, a good knowledge of major whitewater kayaking sites which allows them to use their own judgment to rate each alternative site in terms of a set of attributes (further detail on how these variables were measured is shown in Table 1). The attributes chosen for use 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, reliability of water information, travel distance to site, and travel time to site.

The sampling frame was provided by two Irish kayaker email 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 email addresses was selected, and questionnaires were emailed to these individuals, who were asked to complete and return the questionnaire via email. As an incentive to get people to return the surveys a raffle was organized with €500 worth of kayaking equipment as prizes. Everyone who returned a completed questionnaire had their name entered into the draw. To widen the sample in terms of representativeness and increase the number of completed surveys, the questionnaire was also posted up 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.

The survey instrument included questions about the frequency and costs of kayaking trips to the 11 different kayaking sites. Specifically, respondents were asked how many paddling trips they had taken in the previous 12 months to each of the 11 areas; to score each area in terms of the 9 attributes used; to provide a ranking of attributes; to provide information on spending related to kayaking and to provide information on their kayaking abilities and experience. Other questions related to standard socio-economic information such as employment status and age. Respondents were also asked to indicate what their main occupation was, if they were not currently in full time education. A sample of 279 useable responses from kayakers was acquired. Table 2 presents some further summary statistics of the respondents in the survey.

In the travel cost model literature, travel cost has always been viewed as a very important attribute (hence the name of the model), as it provides the key to obtaining consumer surplus estimates for changes in recreation site quality or availability. Many researchers include travel time along with petrol costs as one element of travel costs (Feather and Shaw, 1999). Indeed this is the approach that we adopt here. Travel distance was converted into travel costs using a per-mile cost of €0.25 which reflects the Automobile Association (AA) of Ireland's calculations for the marginal costs of motoring for a car of average size. Most recreation demand studies use a fraction of the wage rate extracted from the gross income variable for the sample population, in calculating the opportunity cost of travel time. This is then added to each individuals petrol costs to calculate overall travel cost. However, we use each kayakers potential hourly wage, as predicted by an earnings model from a secondary dataset (the European Community Household Panel dataset) and based upon that persons actual socio-economic characteristics to calculate the opportunity cost of time[1]. Once we have calculated the opportunity cost of leisure time, the total travel cost is then calculated by:

$$TC_{ij} = ((2^* (\text{distance} * €0.25))/2.3) + ((\text{travel time}/60) * HW_i) \quad (10)$$

Where TC_{ij} is the travel cost of kayaker i to whitewater site j and HW_i is the predicted potential hourly wage rate of kayaker i. It is usual for the petrol expenses of a kayaking trip to be divided amongst all the participating passengers in the vehicle traveling to the whitewater site. It was found that the average number of kayakers per vehicle was 2.3 individuals.

4.1 Rationale for modelling preference heterogeneity in the kayaking community

Within the sport of whitewater kayaking there are a number of different specialisations, which can help in developing the rational for the expected differences

[1] For an extensive discussion of the methodology used to calculate the travel cost variable in this paper see Hynes et al. (2005)

in preferences amongst kayakers of different skill and experience levels. *River running* involves the use of a paddle to negotiate ones 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 suites their skill level. Table 3 presents the grade of each of the whitewater sites in our survey. *Freestyle kayaking* is when kayakers go "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 would be considered safer than river running.

Whitewater kayakers could also be categorised by the competitive aspect of the sport he or she is (or has been) involved in. *Long distance "k-boat" kayakers* or *kayak polo enthusiasts* will enjoy rivers of lower grade. *Slalom kayakers* and *wild water racers* will favour 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 be probably favour park and play kayaking rather than river running. While these are all distinct disciplines there may be considerable overlap. It would not be uncommon for instance to find a top rodeo kayaker participating in river running or a polo player kayaking at his favourite local playspot. Nevertheless within the whitewater kayaking community a kayaker would usually be categorised by her peers as being either a river runner or a freestyle playboater.

We will now attempt to outline our expectations on the different preferences we would expect for the whitewater site attributes for kayakers from different backgrounds and with different skill and experience levels. Generally speaking, most kayakers should favour better parking facilities at whitewater sites. Having said that, Hynes et al. (2005) have argued that for kayakers, the quality of parking could be taken as a proxy for remoteness, which we would expect may be valued by some kayakers. If this is the case, we might expect some river runners and kayakers with more years of experience to favour more wilderness kayaking excursions that might be associated with poorer parking facilities.

The star rating of the whitewater site indicates whether, within its grade, the site is a particularly good example. For example, the Roughty river in Co. Kerry receives three stars in the Irish Whitewater Guidebook (MacGearailt,1996) as it is one of the classic grade 4 whitewater runs in the country. Basic and intermediate skill kayakers may not be concerned with star rating but may be more interested in a “nice day out” as one of the respondents put it or “good company and good craic” as another put it when asked in the questionnaire “In your opinion, what other factors are important in choosing a site to kayak at?”. Similarly, freestyle kayakers will probably not be overly concerned with the star rating of a feature. In comparison, advanced level kayakers are more interested in the physical features of the whitewater; the gradient; the technical difficulty of the rapids; the presence of standing waves; waterfalls, etc. Taking this into account we would expect advanced skill kayakers and river runners to be more concerned with the star rating of the run than their basic or playboater counterparts.

For the water quality attribute we would expect that all types of kayaker would prefer better quality water to kayak in. Higher skilled paddlers or freestyle kayaker who might spend more time under water and rolling their kayak should be particularly in favour of cleaner water. We would expect that all kayakers would favour quality scenery at the whitewater sites. However, we might expect river runners and advanced skill level kayakers to be more concerned with the quality of the whitewater and to be concentrating on getting through the technically challenging whitewater than on the quality of the scenery around them. On the other hand, long distance or polo kayakers may visit a whitewater site just for the beauty of the area surrounding the whitewater site.

Knowing the water levels at a whitewater site prior to visiting them is an important issue for kayakers and we would expect that all kayakers would favour better prior information. Water levels in Irish rivers are directly determined by rainfall. For this reason, winter tends to be the best time of year for whitewater kayaking. Rainfall, though, can be very localised. As well as this, freestyle kayakers may need even more information on water conditions at their favourite playspots as these locations may be effected by the height of the tides. For example, Curragower wave on the Shannon River is situated near the estuary of the river and only works on the 2 hours either side of low tide. Also, kayakers with more years of experience may be better judges of likely water conditions on rivers and therefore may not need the same levels of prior information compared to kayakers with little experience.

5. Results

We estimate a Random Parameter Logit (RPL) model and a latent class (LC) model. In all models, the choice probabilities of going to whitewater kayaking sites are regressed on travel cost, and the six site attributes; parking, crowding, star rating, water quality, scenery and prior information on water levels. The other regressors are dummy variables for all whitewater kayaking sites, except the Liffey. The models were estimated in Limdep using Maximum Likelihood estimation procedures.

5.1 Results from the random parameter logit model

The results for this model are presented in Table 4. For our RPL model we assume that each whitewater site attribute acts independently on the kayaker's utility (in other words no cross effects are present). The estimated coefficients for the travel cost variable and the whitewater site choice dummies are specified as fixed, to aid estimation. Running the RPL model requires an assumption to be made about the distribution of preferences for each attribute. The main candidate distributions are normal and log normal. The former allows preferences to range between positive and negative for a given attribute, the latter restricts the range to being of one sign only. In particular, as the trip cost coefficient was expected to be negative for each individual, a chosen negative lognormal distribution would eliminate the possibility of finding non-rational behavior in the model. We experimented with allowing some of the coefficients to follow a log-normal distribution. One would suspect that kayakers would appreciate better quality scenery not worse, or cleaner water to kayak in rather than displaying a preference for more polluted water. In these cases a log-normal distribution should be more appropriate. However, when specifying these variables to be log-normally distributed, we failed to get the model to converge. Brownstone &

Train (2003) experienced the same problem. Therefore, our model treats all coefficients as random and normally distributed.

Mean effects for the quality of parking, star quality, water quality, prior information and scenic quality are all of the expected sign and significant at the 5% level.. Unexpectedly the crowding coefficient has a negative sign and is significant at the 5% level, indicating that the more crowded a whitewater site is, the more kayakers favour it. This may be true over a certain range, as kayakers prefer company on the whitewater runs, but we would expect that when crowding reaches a certain threshold it would have a negative impact on the kayaker's utility function. Perhaps it is the case that this threshold level is not reached or has not been experienced by the kayakers in the sample, at the eleven whitewater sites. Indeed, in general, overcrowding is not a major problem at the majority of Irish whitewater sites.

The significance of the parameters on the standard deviations of the site choice coefficients shows whether taste differences vary significantly across the kayaking population. Since the estimated standard deviations of the coefficients for the site choice attributes are all significant at the 5% level, this would seem to indicate that these parameters do indeed vary considerably in the population. Part of this variation in preferences could perhaps be captured by characteristics of the kayakers, which are not included in the model. However, in a RPL model of appliance choice, Revelt and Train (1998) found considerable variation still remained even after including demographic variables. This would suggest that preferences vary considerably more than can be explained by observed characteristics of people. The whitewater site dummies are all significant and they all sites display a negative sign.

The results of the RPL are quite similar in sign and magnitude to the standard random utility (multinomial logit, or MNL) model where preferences are assumed to be homogenous (see appendix A). The travel cost coefficient for the standard MNL is -0.069 whereas it is –0.063 for the RPL. The MNL also contains all negative and significant site choice dummies with similar magnitudes to the RPL results. The major difference between the two models is with regard to the parking, water quality and crowding coefficients. The MNL, unlike the RPL model, displays the expected sign for the crowding variable but a negative sign for the parking variable. Finally, the water quality variable, even though it is of the expected sign, is found to be insignificant in the MNL whereas it is highly significant in the RPL model.

5.2 Results from the multinomial logit latent class model

The conventional specification tests used for maximum likelihood estimates (likelihood ratio, Lagrange multipliers and Wald tests) are not valid in the context of latent class models 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) and used in the application of a recreational latent class model by Scarpa and Thiene (forthcoming). The information criteria statistic (C) is specified as $-2lnL + J\delta$ where lnL 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 $\delta = 2$ we obtain the Akaike Information Criteria (AIC); for $\delta = \ln(N+1)$ we obtain the consistent AIC (cnAIC); for $\delta = \ln(N)$ we obtain the Bayesian Information Criteria (BIC), which by construction is very similar to the cnAIC. 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 are, they can fail some of the regularity conditions for a valid test under the null (Leroux, 1992). As such, Scarpa and Thiene point out 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”.

The values for selected information criteria of different preference-groups are reported in Table 5 and are consistent with the hypothesis that there are at least 4 classes with satisfactory parameter estimates, in both statistical and theoretical terms..

For the sake of space we omit the presentation of all the model estimates. We hence only present the LCM estimate for 4 classes. 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 kayaking experience (number of years kayaking) as well as the kayak handling skill of the kayaker[2]. A correlation coefficient of 0.66 indicates that there is a strong positive linear relationship between the experience and skill variable in our data set. In addition to a complete set of whitewater site attribute coefficients being estimated for each latent class, a set of probabilities for each class were estimated assigning class membership as a function of the kayaker's experience and his or her level of kayak handling experience. For these characteristics the number of coefficients estimated has to be equal to the number of latent classes minus one in order to account for the indeterminacy in the model, which is caused by the lack of normalization (Hilger, 2002).

The results of the latent class model with 4 class segments (Model 4L) are presented in table 6. Restricting the coefficients on the whitewater site choice dummies to be equal across classes yields 7 (out of 10) whitewater site dummy coefficients that are statistically significant and of the expected sign. This model also provides coefficients that are significant for all the whitewater site attribute variables except water quality in class C. Class B's attributes are significant except for the parking quality, crowding and star rating coefficients. The quality of water and quality of scenery are the only significant attributes in class D and class A has no significant site attributes at all. Even the travel cost variable is of the unexpected sign in class A. Also, there is a wide variation in the signs of the coefficients across classes indicating very different preference patterns among the kayaking population.

The negative sign for the star quality variable in class C may seem surprising, indicating that kayakers prefer lower star quality whitewater sites. However, we may expect some kayakers to prefer lower star quality whitewater sites, as these

[2] The skill variable is 0 if the kayaker has basic or intermediate kayak handling skills and 1 if he or she has advanced kayak-handling skills.

whitewater sites are less technically difficult and may result in a more pleasant paddle for kayakers with less experience. Also, it should be kept in mind that "playboaters" are not concerned in general with the star rating of a whitewater site as they are only concerned with one "park and play" feature at the site.

Although some case may be made for a negative sign on the crowding variable (kayakers preferring crowds on the river as they are social creatures!), it is very difficult to make a case for a group of kayakers preferring poorer water quality at whitewater sites (classes C and D display a negative sign on the water quality coefficient). Having said that kayakers do not in general take much notice of the quality of the water they paddle in unless the pollution levels are extreme. Indeed, the most frequented white water site in the sample was the "Sluice" whitewater site on the river Liffey. This is the most polluted of the whitewater sites looked at in this analysis. Similarly, it is hard to justify a group of kayakers preferring worse scenery but yet this would appear to be the case for class A and B. The fact that parking has a negative sign for classes C and D could be interpreted as showing that the remoter or more secluded the whitewater site is, the higher the probability the site will be visited by these classes.

For our restricted model of Table 6, we would speculate that class C is representative of the less experienced, basic or intermediate skilled *river running* kayaker, favouring remote runs, lower star quality runs, good scenery and good prior information on water levels. This would be in keeping with the image of this type of kayaker, where he is interested in a lazy stroll down the relatively slow moving, uncrowded river. Class D kayakers could be thought of as the more experienced, *river running* kayakers. From the estimated coefficients it can be seen this group prefer more remote (negative parking coefficient), higher star quality runs. They also prefer more scenic whitewater sites and seem to be unconcerned about prior information on water levels before they make a trip. These individuals have more experience and a better understanding of where good water levels may be found so prior information on water levels is not as important for this group as it is for the less experienced river runner described by group C..

Class A kayakers could be thought of as the "*competitive, long distance"* kayakers. From the estimated coefficients it can be seen this minority group would appear to be unconcerned about the attributes of the river. They simply require a venue to train and race on. Also judging from the unusually positive sign on the travel cost variable they do not even mind travelling large distances to get to the racing sites. The probability of any kayaker in our sample being described by this class is extremely low at only 0.003. Finally, we would speculate that class B represents the *freestyle playboaters*. As can be seen from the coefficients these kayakers prefer (as we would expect) better parking facilities, proper prior information on water levels and uncrowded playspots. Given the amount of time this group spends under water and rolling their kayaker, we find as expected that this group of kayakers is positively concerned with water quality.

The individual specific posterior class probabilities were calculated as outlined in section 3. The average individual specific posterior class probabilities for class segments A, B, C and D were found to be 0.003, 0,53, 0.31 and 0.16 respectfully. This indicates that within our sample, kayakers have a 50% chance of having the preferences described by the latent class B parameters. We utilise 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 impact of a number of whitewater site changes.

6. Welfare Impacts of Site Changes

In this section, we consider a number of welfare scenarios for our alternative models. These include: (a) The Roughty river becoming unnavigable by kayak due to the building of a hydro scheme, (b) The Boyne river becoming unnavigable by kayak due to the building of a hydro scheme, (c) A 25% improvement in water quality at the Curragower wave on the Shannon and (d) A €3 parking fee at the put-in to the Boluisce river. The results based on both models are shown in Tables 7. All results are per kayaker per trip. The expected CV loss per trip per site is calculated using equation 8. The 2 columns of table 7 present the welfare estimates for the RPL model and the LC model containing 4 classes.

The expected CV loss per kayaker from the loss of the Roughty river is calculated at €2.78 when we use the results of the RPL model. The corresponding estimate when we use the results of the LC model is much higher than this at €36.72. A less extreme difference is found when we calculate the welfare loss associated the closer of the Boyne river to whitewater kayaking. The expected CV loss per kayaker from the loss of the Boyne river is calculated at €26.22 when we use the results of the RPL model. The corresponding estimate when we use the results of the LC model is almost double the RPL welfare estimate at €55.01. These results may be accounted for by the fact that the Boyne river is a lower grade river more likely to be frequented by less experienced and less skilful kayakers (those in class C) whereas the Roughty is a grade run that would be frequented by kayakers of higher skill and more whitewater experience (class D). The average probability of a kayaker being in class C or class D is relatively high at 0.47 (0.31 and 0.16 respectively). A relatively high weight is therefore attached to these classes in the calculation of the welfare estimate. Also the travel cost coefficient values associated with these two classes are much lower than the travel cost coefficient for the RPL, -0.264 and 0.676 compared to –0.063. This leads to the welfare estimate for the loss of the whitewater sites from the choice being much larger when estimated by the LC model compared to when they are estimated from the RPL model.

In relation to changes in the attributes of particular sites, the LC model, once more, gives higher estimates of the welfare impacts on whitewater kayakers. For instance the estimate of the welfare gain to kayakers, of a 25% water quality improvement at the Curragower wave on the river Shannon using the LC model is €14.50. However, the estimated recreational benefit is only €0.55 per kayaker per trip when using the RPL results. The local county council may be more willing to undertake a water clean-up program in Limerick city if presented with the first estimates whereas they may be unlikely to if presented with the second. Similarly, the loss in kayaker welfare per trip when a €3 parking fee is imposed at the put-in to the Sluice on the river Liffey is 43% less if one uses the RPL model instead of the LC model results, €3.70 compared to €5.49.

7. Conclusions

This paper examined alternative ways of modelling heterogeneity of tastes for attributes of an outdoor recreational good via a travel cost survey. We contrasted two advanced modelling 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 the loss in certain whitewater kayaking sites and changes in the quality of the kayaking experience at these sites in Ireland due to changes to certain attributes at the sites. The results of the RPL model gives considerably lower welfare estimates of consumer surplus than the LC model when analysing changes in the attributes of particular sites. We would argue that by not taking into account different preferences of different types of kayakers or the different type of recreationalist that frequent different recreational sites in general, recreation demand modellers may be underestimating (overestimating) the welfare losses (gains) associated with changes in site attributes.

The random parameter logit approach has some intuitive attraction in so far as it allows explicitly for a range of attitudes towards attributes within the population, identifies which attributes have significant levels of heterogeneity in preferences, and quantifies the degree of the spread of values around the mean. This is important in circumstances such as the one presented here where we are interested in the demand for recreation service flows by a certain set of individuals whose attitudes and tastes in relation to their recreational activity vary considerably. However, the analyst must impose a distributional form on preferences. A simple normal distribution for preference parameters allows both positive and negative attitudes towards an attribute. However, in some cases, such as for water quality, one may suspect that they should be uniformly negative or positive, in which instance one requires some restriction on the distribution. Our model, however, failed to converge when we attempted these restrictions.

The latent class model provides further insight into the data by endogenously identifying groups of kayakers who have similar preferences for particular whitewater site attributes, but where preferences vary considerably between groups. In our latent class analysis we found statistical evidence in favour of the existence of four distinct preference groups. We believe that an immediate interpretation of the differences between groups is possible based on knowledge of the different types of kayakers in the Irish whitewater community. While most preference structures in the classes are consistent with theoretical expectations in terms of signs, groups representing small fractions of the sample tend to show much lower significance of parameter estimates. The latent class approach generates additional information which is potentially very useful to recreational site managers for a wide range of purposes. For example, knowing that *freestyle playboaters* are likely to be the only group of kayakers found at a site such as Clifden play hole allows us to concentrate on the parameter estimates of class B in our LC model when budgeting maintenance or improvement plans for this whitewater destination.

As Scarpa and Thiene (forthcoming) point out there is no unambiguous test of the superiority of one approach (RPL or LCM) over the other. However, we believe that the LCM approach may offer a much more in-depth understanding of the heterogeneity of recreationalist preferences that are not readily identifiable through the random parameter logit model. The latent class model, put simply, provides a greater range of potentially-useful information. Randall (1997) foresaw the changes in non-market 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 paper has presented two possible methodologies that attempt to implement Randall aspirations. We would argue that the latent class method has a slight advantage over the RPL approach, 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. This trait of the LC model is the main reason that it likely to become an important tool for resource managers in the future.

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Table 1. Measured Attributes of Whitewater Sites and the Attribute Levels

Factor	Score/Level of Factor				
Average quality and safety of parking at the site (Score from 1 = poor to 5 = excellent).	1	2	3	4	5
Average crowding at the paddling site (How many other kayakers are on the water you are paddling- Score from 1 = very crowded to 5 = uncrowded)	1	2	3	4	5
Average quality of the kayaking site (i.e. No. of stars).	0 star	1 stars	2 stars	3 stars	
Average quality of the water (Score from 1 = extremely polluted to 5 = unpolluted).	1	2	3	4	5
Scenic quality of the kayaking site (Score from 1 = not at all scenic to 5 = very scenic).	1	2	3	4	5
Reliability of Water (score from 1 = before visiting the site, completely unsure of water level at the site to 5 = positive about water level at the site)	1	2	3	4	5

Table 2. Summary Statistics of Respondents in Kayaking Survey

	Mean	Std. Dev.	Min	Max
Age	27.06	7.20	16	52
Education	1.27	0.48	1	3
Income	27554.35	21891.34	5000	90000
Importance of Kayaking*	1.26	0.71	1	4
Travel Cost	55.59	37.64	1.15	274.79
Obligation Free Days	102.88	70.71	0	365
Number of Years Paddling	7.22	6.27	0.5	36

*1 indicates that kayaking is the respondents most important outdoor activity whereas 4 indicates that kayaking is but one of many outdoor pursuits participated in by the respondent.

Table 3. Whitewater Sites and Associated Whitewater Grade

Kayaking Site	*Grade*
The Liffey	2/3
Clifden Play Hole	2
Curragower Wave	3
The Boyne	2/3
The Roughty	4
The Clare Glens	4/5
The Annamoe	3
The Barrow	2
The Dargle	4/5
The Inny	2

The Boluisce	2/3

Grades from the Irish Whitewater Guide book (MacGearailt, 1996)

Table 4. Random Parameters Logit Model, all trips

Variable		*Coefficient*	*St. Error*
Random Parameters in Utility Functions			
Quality of Parking	Mean of coefficient	0.220	0.022*
	Stnd. Dev. of coefficient	0.382	0.058*
Crowding	Mean of coefficient	-0.215	0.022*
	Stnd. Dev. of coefficient	0.782	0.043*
Star quality of the whitewater site	Mean of coefficient	0.546	0.033*
	Stnd. Dev. of coefficient	1.000	0.056*
Water Quality	Mean of coefficient	0.260	0.025*
	Stnd. Dev. of coefficient	0.230	0.070*
Scenic quality	Mean of coefficient	0.275	0.024*
	Stnd. Dev. of coefficient	0.590	0.042*
Availability of Information on water levels	Mean of coefficient	0.278	0.025*
levels prior to visiting the site	*Stnd. Dev. of coefficient*	0.700	0.048*
Nonrandom Parameters in Utility Functions			
Travel Cost		-0.063	0.001*
Clifden Play Hole		-1.999	0.102*
Curragower Wave on the Shannon		-1.738	0.067*
The Boyne		-1.601	0.054*
The Roughty		-2.560	0.117*
The Clare Glens		-4.130	0.115*
The Annamoe		-2.598	0.069*
The Barrow		-3.186	0.095*
The Dargle		-4.577	0.105*
The Inny		-2.829	0.086*
The Boluisce (Spiddle)		-2.899	0.101*

* indicates significant at 5%, RPL Model has log likelihood value of –15,912.37.

Table 5. Criteria for Number of Classes

		N=279			
Number of Classes	lnL	Parameters	AIC	BIC	crAIC
1	-16192.96	17	32384	-34	-64768
2	-2481.54	34	4963	-68	-9926
3	-2266.19	51	4532	-102	-9065
4	-2184.03	68	4368	-136	-8736
5	-2218.67	85	4437	-170	-8875

Table 6. Latent Class Model (4L), latent classes A, B, C and D

	Latent Class A		**Latent Class B**		**Latent Class C**		**Latent Class D**	
Variable	*Coefficient*	*St. Error*	*Coefficient*	*St. Error*	*Coefficient*	*St. Error*	*Coefficient*	*St. Error*
Travel Cost	0.765	2738729	-0.037	0.010*	-0.264	0.036*	-0.676	0.172*
Quality of Parking	22.789	9780169	0.005	0.140	-0.970	0.304*	-1.649	1.958
Crowding	5.814	5940854	0.033	0.171	2.211	0.353*	1.443	1.452
Star quality of the whitewater site	11.234	6517027	0.464	0.298	-2.000	0.564*	2.080	0.866
Water Quality	19.822	6209869	0.318	0.138*	-0.718	0.468	-3.467	1.379*
Scenic quality	-3.482	7284839	-0.914	0.172*	2.243	0.587*	3.305	1.002*
Availability of Information on water levels	-45.381	8083810	0.373	0.115*	3.329	0.584*	0.971	2.178
Clifden Play Hole	-4.185	0.646*	-4.185	0.646*	-4.185	0.646*	-4.185	0.646*
Curragower Wave on the Shannon	-6.250	0.570*	-6.250	0.570*	-6.250	0.570*	-6.250	0.570*
The Boyne	-18.997	1.717*	-18.997	1.717*	-18.997	1.717*	-18.997	1.717*
The Roughty	-28.728	682.950	-28.728	682.950	-28.728	682.950	-28.728	682.950
The Clare Glens	-27.234	267.168	-27.234	267.168	-27.234	267.168	-27.234	267.168
The Annamoe	-16.810	6.393*	-16.810	6.393*	-16.810	6.393*	-16.810	6.393*
The Barrow	-17.463	4.574*	-17.463	4.574*	-17.463	4.574*	-17.463	4.574*
The Dargle	-22.930	15.602	-22.930	15.602	-22.930	15.602	-22.930	15.602
The Inny	-10.197	0.578*	-10.197	0.578*	-10.197	0.578*	-10.197	0.578*
The Boluisce (Spiddle)	-22.741	2.308*	-22.741	2.308*	-22.741	2.308*	-22.741	2.308*
Class Probability								
Experience	-3.079	52.366	0.137	0.065	-0.048	0.069		
Kayak Handling Skill	-1.723	7930.570	3.902	8.756	5.650	8.786		

* significant at 5%, LC Model (4L) has log likelihood value of –2,184.029

Table 7. Welfare Impact of Different Policy Scenarios as measured by loss/gain in Consumer Surplus per kayaker per visit

Scenario	RPL Model (€)	4L LC Model (€)
Loss of the Boyne river due to the building of a hydro scheme	26.22	55.01
Loss of the Roughty river due to the building of a hydro scheme	2.78	36.72
25% improvement in water quality at Curragower wave	0.56	14.50
€3 parking fee at the Liffey	3.70	5.49

Source: Calculated from models reported in Tables 4 and 6.

Appendix A.

Table A. Random Utility Site Choice, all trips

Variable	All Kayakers
Travel Cost	-0.069 (17.98)**
Quality of Parking	-0.145 (2.04)*
Crowding	0.153 (2.19)*
Star quality of the whitewater site	0.351 (2.82)**
Water Quality	0.142 -1.39
Scenic quality	0.285 (2.99)**
Availability of Information on water levels	-0.08 -0.92
Clifden Play Hole	-0.905 (2.47)*
Curragower Wave on the Shannon	-1.413 (5.34)**
The Boyne	-1.772 (5.93)**
The Roughty	-1.641 (4.10)**
The Clare Glens	-3.387 (8.63)**
The Annamoe	-2.076 (6.25)**
The Barrow	-2.914 (9.27)**
The Dargle	-5.011 (12.33)**
The Inny	-1.769 (6.04)**
The Boluisce (Spiddle)	-2.344 (6.96)**

Absolute value of z statistics in parentheses; * significant at 5%; ** significant at 1%.