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Published in:

Document Version:
Peer reviewed version

Queen's University Belfast - Research Portal:

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Abstract

This paper compares the Random Regret Minimization and the Random Utility Maximization models for determining recreational choice. The Random Regret approach is based on the idea that, when choosing, individuals aim to minimize their regret − regret being defined as what one experiences when a non-chosen alternative in a choice set performs better than a chosen one in relation to one or more attributes. The Random Regret paradigm, recently developed in transport economics, presents a tractable, regret-based alternative to the dominant choice paradigm based on Random Utility. Using data from a travel cost study exploring factors that influence kayakers' site-choice decisions in the Republic of Ireland, we estimate both the traditional Random Utility multinomial logit model (RU-MNL) and the Random Regret multinomial logit model (RR-MNL) to gain more insights into site choice decisions. We further explore whether choices are driven by a utility maximization or a regret minimization paradigm by running a binary logit model to examine the likelihood of the two decision choice paradigms using site visits and respondents characteristics as explanatory variables. In addition to being one of the first studies to apply the RR-MNL to an environmental good, this paper also represents the first application of the RR-MNL to compute the Logsum to test and strengthen conclusions on welfare impacts of potential alternative policy scenarios.

Keywords: Random Regret Minimization; Random Utility Maximization; site choice probabilities; Recreational demand.

1.   Introduction

The use value of recreational activities of bathing, boating, fishing, hiking, camping, kayaking, horseback riding, and cycling within natural resource systems such as beaches, rivers, lakes, parks, and mountains has been widely investigated using the travel cost model. After Hotelling's (1947) intuitive recreation demand model, and initial works by Clawson (1959), Trice and Wood (1958), and Burt and Brewer (1971), Hanemann (1978) presents the first application of the Random Utility Model (RUM) to analyse the demand for recreation when users have to choose among several alternative sites to visit. Since then, the RUM has been widely used to model the demand for recreation (e.g. Bockstael et al, 1987; Morey et al, 1993; Parsons and Kealy, 1995; Chen and Cosslet, 1998; Herriges and Kling, 1999; Romano et al, 2000; Phaneuf et al, 2000; Freeman, 2003; Parsons, 2003; Phaneuf and Smith, 2005; Bockstael and McConnell, 2007, Hynes et al., 2008).

On a given choice occasion, the RUM models the site-choice of one out of a number of alternative sites, as a function of attributes of the site, and central to its application, it assumes that a user visits the site that gives him/her the highest utility (Haab and McConnell, 2002). As it is widely acknowledged, the RUM's popularity is mainly due to its strong economic foundations, its conceptual elegance and its formal tractability. Many RUM based models have closed-form formulations for choice probabilities, and most can be easily coded and estimated using standard discrete choice-software packages. However, some observers have pointed out that at least some of the assumptions behind the RUM might lack in behavioural realism. For example, research from psychology and consumer behaviour claims that decision-makers process information through limited capabilities and resources, trying to make the best possible choices within operational constraints (Ford et al, 1989).

Various attempts have been made to relax the RUM assumptions, mostly by adapting the RUM, rather than by proposing completely new representations of the choice process. For example, Swait (2001) and Arentze and Timmermans (2007), among others, proposed a model to relax the assumption of fully compensatory behaviour – a decision rule by which positive evaluation of an attribute compensates for a negative evaluation of another attribute. Kivetz et al. (2004) and Zhang et al. (2004) developed a setting to accommodate for the sensitivity to choice set composition. Resulting models, however, are, without exceptions, less parsimonious and less tractable than the RUM's workhorse, the Mixed Multinomial Logit model. Furthermore, they generally require researchers to develop specific-purpose code for estimation.

As an alternative to the RUM, this paper employs the Random Regret Minimization Model. This is a relatively new choice paradigm that relaxes the assumption of utility maximization – and of fully compensatory decision makers – while remaining econometrically as parsimonious and tractable as its utilitarian counterpart, the RUM (Chorus, 2010). The Random Regret Minimization Multinomial Logit model (RR-MNL) is built on the idea that, when choosing, individuals aim to minimize their regret rather than to maximize their utility – regret being defined as what one experiences when a non-chosen alternative performs better than a chosen one, on one or more attributes. There is much empirical evidence for this behavioural premise. The idea that regret is an important determinant of choice behaviour is not new and is well established theoretically and empirically in many fields, including marketing (e.g. Simonson, 1992; Zeelenberg and Pieters, 2007), microeconomics (e.g. Loomes and Sugden, 1982; Sarver, 2008), psychology (e.g. Zeelenberg, 1999; Connolly, 2005), the management sciences (e.g. Savage, 1954; Bell, 1982) and transportation (e.g.,

Chorus et al., 2006, 2009).[1] The Random Regret Minimization Model implies semi-compensatory behaviour: improving an alternative in terms of an attribute on which it already performs well relative to other alternatives generates only small decreases in regret, whereas deteriorating to a similar extent the performance on another equally important attribute on which the alternative has a poor performance relative to other alternatives may generate substantial increases in regret. As a result, the extent to which a strong performance on one attribute can make up for a poor performance on another depends on the relative position of each alternative in the choice set. This choice set composition-effect, which has been well established empirically in the field of consumer choice (e.g. Kivetz et al., 2004), is called the compromise effect. This effect states that alternatives with an 'in-between' performance on all attributes, relative to the other alternatives in the choice set, are generally favoured by choice-makers over alternatives with a poor performance on some attributes and a strong performance on others.[2] What is new about the Random Regret Minimization approach to Logit models is that it translates this conceptual notion of regret minimization into an

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[1] Using neuroimaging techniques, Coricelli et al. (2005) show that the area of the human brain that is active when decision-makers experience regret after having made a (poor) choice, is also highly active split seconds *before* they make a choice. In their words "anticipating regret is a powerful predictor of future choices".

[2] The compromise effect indicates an anomalous choice behaviour that happens when the addition of an extreme option to the choice set shifts the choice preferences in favour of the compromise option (Chen and Rao Hill, 2009). Simonson (1989) has reported that the compromise effect is stronger when people are expected to justify their choices to others, or when they are uncertain about their preference toward specific attribute values. The compromise effect has been frequently observed in consumer choice (Dhar and Simonson 2003) and has had practical implications in areas such as new product introduction, positioning strategy, and product assortments (Kivetz et al 2004; Simonson and Tversky 1992).

operational, easily estimable, discrete choice model for the analysis of risky and riskless choices.[3]

In this paper, we explore how the RR-MNL can be used to determine site-choice for recreational goods by modelling travel cost data elicited from a sample of kayakers in the Republic of Ireland. We further explore whether choices are driven by a utility maximization or a regret minimization paradigm by running a binary logit model to explain the likelihood of the two decision choice paradigms using site visits and respondents characteristics as explanatory variables. To our knowledge, this is the first application of the RR-MNL to a revealed preference dataset eliciting recreation site-choice. Furthermore, this is the first attempt to assess, at the choice level (as opposed to the overall model fit[4]), which model, the Random Utility Maximization multinomial logit model (RU-MNL) or the RR-MNL, better describes the decision process underlying each choice. This novel application of the model potentially reveals very useful information for policy makers interested in the management of recreational sites. This paper is also one of the first attempts to compute the Logsum based on RR-MNL and to compare it to the Logsum based on RU-MNL to assess the impacts of hypothetical changes to the quality of recreational sites.

The remainder of the paper is organized as follows. Section 2 describes the two modelling approaches. Section 3 provides an overview of previous studies that compare RR-MNL to RU-MNL in choice modelling. Section 4 describes the survey design and the dataset. Section

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[3] As noted by Thiene et al. (2011), although the RR-MNL paradigm shares with the well-known Regret Theory (Loomes and Sugden, 1982; Loomes and Sugden, 1983; Quiggin, 1994) its consideration of regret as an important determinant of decisions, the two approaches differ on a number of aspects (for more details see Thiene et al., 2011).

[4] We do not consider the individual level, as in this context we consider the choice level more important for policy makers and stakeholders.

5 presents the empirical analyses providing a comparison of RR-MNL and RU-MNL in terms of goodness of fit and welfare analysis. Section 6 presents conclusions and discusses potential avenues for further research.

2. Modelling site choice decisions: Regret vs. Utility

Modelling Utility and Regret

This section describes the Random Utility Maximization model and the Random Regret Minimization model. Consider a situation in which a respondent has to choose between *j* alternatives, each of them being described in terms of *m* attributes. Within the RUM approach (Thurstone, 1927; Manski, 1977), the respondent chooses the alternative that maximizes his/her utility function. Therefore, to model a respondent's choice, the analyst focuses his attention on the utility that each single alternative gives to the respondent. The utility function can be written as:

$$U_{ni} = V(\beta, X_{ni}) + \varepsilon_{ni} \tag{1}$$

where *i* is the chosen alternative by respondent *n*, X is a vector of *m* attributes, β is a vector of parameters to be estimated and ε is an i.i.d. error term, representing the unobserved part of the utility, and is Extreme Value Type I-distributed.

Given the utility function of Equation 1, the probability for individual *n* of choosing alternative *i* over any other alternative *j* in the choice set is represented by a RU-MNL model (McFadden, 1974):

$$Pr_{n(i)} = \frac{e^{V_{in}}}{\sum_{j=1}^{J} e^{V_{jn}}}, \tag{2}$$

where $V_{ni} = \beta' X_{ni.}$

On the other hand, the RR-MNL postulates that, when choosing between a set of alternatives, decision-makers aim to minimize anticipated random regret, rather than maximize random utility. The level of anticipated random regret that is associated with the considered alternative i is composed of a systematic regret R_i and an i.i.d. error component η, where the systematic regret R_i can be written as (Chorus, 2010):

$$R_i = \sum_{j \neq i} \sum_{m=1..,M} \ln \left(1 + e^{\theta_m \left(x_{jm} - x_{im} \right)} \right) \tag{3}$$

In equation (3), regret is conceived to be the sum of all so-called binary regrets associated with bilaterally comparing alternative i with all the other alternatives j in the choice set. This comparison is done for all attributes m. From equation (3), we can notice that regret is close to zero when alternative j performs (much) worse than i in terms of attribute m, and that regret increases as i performs worse than j in terms of attribute m. The parameter θ_m captures the slope of the regret-function for attribute m. The parameter θ_m reflects the upper bound of the extent to which a unit increase in the relative performance of an attribute influences the level of regret that is associated with a comparison with another alternative. In other words, the estimated coefficients reflect the potential[5] contribution of an attribute to the regret associated with that alternative. A positive coefficient for an attribute suggests that regret increases when the difference in that attribute between a chosen and a non chosen alternative increases. A negative coefficient for an attribute implies that regret increases when a considered alternative is compared to another alternative with a decreasing value on that attribute. In other words, as suggested by an anonymous reviewer, decreasing attribute-values of a competing alternative lead to increases in regret associated with the considered

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[5] As stated by Chorus et al (2008), "the word potential is important here, since an attribute's actual contribution to regret depends on (i) whether the considered alternative performs better or worse on the attribute than the alternative it is compared with and (ii) whether regret caused by comparing the alternatives is surpassed or not by comparing the considered alternative with another alternative."

alternative when the attribute has a negative sign, such as is the case with the travel cost attribute.

Acknowledging the fact that minimizing the random regret is mathematically equivalent to maximizing the negative of the random regret, the probability for individual n of choosing alternative i over any other alternative j in the choice set is represented by a well-known multinomial logit formulation[6]:

$$Pr_{n^{(i)}} = \frac{e^{(-R_i)}}{\sum_{j=1}^{J} e^{(-R_j)}}, \qquad (4)$$

In contrast with the RU-MNL, the negative of the RR-MNL's random error is distributed Extreme Value Type I. The resemblance between the RR-MNL and the RU-MNL is remarkable. Both models result in logit-choice probabilities and are equally parsimonious: each parameter estimated for a RR-MNL has a counterpart in a RU-MNL. When there are only two alternatives to consider, the RR-MNL and the RU-MNL generate the same choice probabilities.

However, the two modelling approaches exhibit at least two important differences.[7] First, in contrast with its utilitarian counterpart, the RR-MNL does not exhibit the independence of irrelevant alternative (IIA) property. As a consequence, the ratio of choice probabilities of

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[6] As indicated by an anonymous reviewer, in contrast with RU-MNL, the negative of the RR-MNL's random error is distributed Extreme Value Type I. Just like the Random Utility Maximization model, the Random Regret Minimization model is capable of modelling random parameters, interaction effects and other sources of variability in parameters. One exception is the use of alternative-specific weights: since the Random Regret Minimization model is built around the notion that differences in attribute-values across alternatives generate regret, it assumes that the weight that is attached to this difference is generic across alternatives.

[7] See Chorus (2010) for a more in-depth discussion of these differences, using numerical examples and formal proofs.

any two alternatives *i* and *j* depends on the performance of these alternatives relative to one another as well as relative to every other alternative *k* in the choice set. This follows directly from the specification of the regret-function, which postulates that the regret associated with any alternative is a function of its performance relative to each of the other available alternatives. Second, the specification of the RR-MNL implies semi-compensatory behaviour: improving an alternative in terms of an attribute on which it already performs well relative to other alternatives generates only small decreases in regret, whereas deteriorating to a similar extent the performance on another equally important attribute on which the alternative has a poor performance relative to other alternatives may generate substantial increases in regret. As a result, the extent to which a strong performance on one attribute can compensate for a poor performance on another depends on the relative position of each alternative in the choice set.

It is worth emphasizing that the RR-MNL ability to display semi-compensatory decision-making and choice set effects, like the compromise effect, does not come at the cost of added parameters as in the case of other models aimed at capturing these behavioural phenomena (e.g. Kivetz et al., 2004 and Zhang et al., 2004). In fact, these behavioural phenomena emerge from the underlying structure of the RR-MNL, which itself follows directly from the model's underlying behavioral premise – that decision-makers aim to avoid the situation where a non-chosen alternative performs better than a chosen one in terms of one or more of its attributes.[8]

Comparing the two models

Once the RU-MNL and the RR-MNL have been estimated, the next step is to compare the two model fits. In our study we compare the models at a dataset level, as well as at a single

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[8] See Chorus (Forthcoming) for a more in-depth discussion.

travel occasion (choice) level. We accomplish the first objective by performing significance tests of relative model fit by means of the Ben-Akiva and Swait test (1986) for non-nested models.[9] Next we are interested in understanding which one of the two paradigms – regret or utility – better describes each single travel occasion. We are particularly interested in examining which site attributes and respondent characteristics are more likely to better explain a choice by regret or utility. We therefore compute the contribution to the value of the Log-likelihood function for each choice under both the RU-MNL and the RR-MNL. We then create a dummy variable equal to one when the Log-likelihood of the RU-MNL outperforms the Log-likelihood of the RR-MNL, and zero otherwise. Next, we run a logit regression on this variable where the characteristics of the choice, respondent and chosen site are used as explanatory variables:

$$P(d)_{nti} = 1/(1+\exp(-\alpha+\gamma'Z_{nti})) \qquad (5)$$

where d is a dummy variable equal to 1 when the RU-MNL outperforms the RR-MNL in explaining choice t, and 0 otherwise, α and γ are parameters of the logit regression on this variable and Z is a vector representing the characteristics of the choice t, of the respondent n and of the chosen site i. We have little *a priori* expectations on the signs of the coefficient estimates. If the RU-MNL on average outperforms the RR-MNL, then we should expect a positive and significant coefficient for the intercept, suggesting that – all else being equal – choices are better explained by utility maximization. We should also expect that choices of familiar sites and sites visited more often are better explained by utility maximization; hence the coefficients associated with these variables should be estimated with positive and significant signs. Finally, we may expect negative and significant signs for coefficients of

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[9] More specifically, the Ben-Akiva and Swait test to compare two non-nested models, A and B, gives an upper bound for the probability that, when model A achieves a better log-likelihood than model B, A is the correct model. This upper bound can be considered a conservative proxy for the significance of a difference in model fit between two non-nested models A and B.

recreational sites less familiar to the respondents, as their choice may be driven by regret minimization.

Policy analysis

One of the main objectives in analysing recreational demand is to measure the impact of possible hypothetical changes in recreation quality that modify the current situation for some or all of the sites analysed. The Logsum is a widely used measure for assessing user's benefits and for retrieving post estimation welfare values.[10] The RU-MNL Logsum is expressed as the expected value of the maximum utility in the choice situation:

$$LS_{RU} = E\left[max_{j=1\ldots J}\{U_j\}\right] = \int_{\varepsilon} \left[max_{j=1\ldots J}\{U_j\} \cdot f(\varepsilon)\right]d\varepsilon = ln\left[\sum_{j=1\ldots J} exp(V_j)\right]$$

(6)

The RR-MNL Logsum, as shown by Chorus (2011), is computed as the expected value of the minimum regret in the choice situation:

$$LS_{RR} = E\left[min_{j=1\ldots J}\{RR_j\}\right] = \int_{\varepsilon} \left[min_{j=1\ldots J}\{RR_j\} \cdot f(\eta)\right]d\eta = -ln\left[\sum_{j=1\ldots J} exp(-R_j)\right]$$

(7)

To assess the impacts of a hypothetical change in recreation quality for a representative individual, we calculate the difference in the Logsums before and after the change. For the RU-MNL, this calculation is equal to LS_{RU}^1-LS_{RU}^0, where LS_{RU}^0 is the Logsum for the RU-MNL calculated at the current situation, and LS_{RU}^1 is the Logsum calculated for the RU-

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[10] See Ben-Akiva and Lehmann (1985) for an in-depth and more formal presentation of the Logsum.

MNL after the changes in recreation quality. A similar calculation can be performed to compare the Logsums derived from the RR-MNL to assess the impact of a hypothetical change in recreation quality in terms of regret. The RR-MNL Logsum is used as a "shadow-measure"[11] of consumer regret to extract more information from a choice situation, in addition to the consumer surplus measured through the RUM-based Logsum. The two Logsum measures should therefore be used in conjunction as one complements the other for assessing policy changes: the RU-MNL Logsum tells us how utility changes, whilst the regret-based Logsum tells us how regret changes as a consequence of a hypothetical change. In fact, considering that the regret-based Logsum is based on behavioural premises which are different from those underlying the utility-based Logsum, the finding that a particular change in recreational quality at a site (or sites) "does well" in the context of both measures may be considered a sign of the robustness of the underlying policy driving the change. In other words, a policy which increases the expected utility associated with the site choice situation and at the same time decreases the expected regret may be preferred to a policy which results in a similar increase in expected utility while increasing expected regret.

3.   RU-MNL vs. RR-MNL: A review of empirical applications and comparisons.

This section reviews studies that have reported RR-MNL estimations and have compared them to the RU-MNL. The RR-MNL approach to discrete choice modelling has been recently introduced in transportation (Chorus, 2010), but has already been used to model choices among shopping destinations (Chorus, 2010), parking lots (Chorus, 2010), road pricing policies (Chorus et al., in press), departure times (Chorus and de Jong, 2011), travel mode

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[11] This is because the RR-MNL Logsum, been based on regret minimization, is not concerned with consumer surplus, which is indeed the focus of the RU-MNL Logsum (Chorus, Under review).

(Pathan, 2010) and even online dating-profiles (Chorus and Rose, 2011). Only recently has the RR-MNL been used for estimating the demand for recreational activities by Thiene et al. (2011). The majority of these studies, including the latter one, are based on stated preference data. When these authors have compared the relative performance of the RR-MNL with the RU-MNL they have found mixed results, and generally have found small differences across the two models. However, studies that perform validations on hold out data (Chorus, 2010), compute elasticities (Thiene et al., 2011; Hensher et al., in press) or make forecasting for various alternatives (e.g., Chorus and Rose, 2011; Chorus et al., in press; Thiene et al., 2011) highlight non-trivial differences between the two models. In combination, these differences in elasticities and predicted market shares do imply that – notwithstanding that model fit differences are generally found to be very small – the two model forms may in fact lead to markedly different behavioural insights and potential policy implications.

Another important finding is that the model fit of the RR-MNL and of the RU-MNL may differ fairly substantially within the segments of the sample that is used for estimation. For example, Chorus and Rose (2011), in a study of online dating preferences, find that for men the RR-MNL fits the data better than the RU-MNL - the difference being highly significant - while for women the two models fit the data equally well. Thiene et al. (2011) find that while mountain-bikers' destination choice behaviour seems to be better described by RR-MNL than by RU-MNL, the opposite is the case for other users of the nature park such as hikers, climbers, visitors who mainly use via-ferratas[12] and visitors who are engaged in short walks and/or picnicking.

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[12] Via-ferratas are challenging trails with metal ropes and ladders designed to help climbers to access vantage points or the top of a mountain in order to enjoy viewscapes.

When comparing RU-MNL and RR-MNL in a revealed preference analysis, Chorus (2010) finds that RR-MNL outperforms RU-MNL. Although one should not generalize the evidence from this small number of studies, the fact that revealed preference data work well for RR-MNL may be explained by the literature from the field of consumer choice. The psychology literature suggests that regret can play an important role when: a) choices are perceived as important and difficult, such as when a person has to choose between dozens of alternatives described by a large set of attributes and levels (pension schemes, car insurance policies, health insurance policies), and b) the decision-maker expects to receive feedbacks about chosen and non-chosen options, such as when someone choice may affect someone else's welfare (Zeelenberg and Pieters, 2007). These considerations can help us understand why RR-MNL may work well in analysing the demand for recreation in a revealed preference context. When a person decides to visit a recreational area, her decision may affect the welfare of the parties that will be travelling with her. The choice of a recreational site may also be quite difficult, as the choice set may contain several alternative sites which can be described by many attributes and levels.

In addition, the studies that have compared RU-MNL and RR-MNL have highlighted that the comparison should not only be based on goodness of fit of the two models. The two choice paradigms are able to capture different aspects of the choice behaviour. The RU-MNL is able to model choices based on utility maximization, whilst the RR-MNL is able to explain choices based on regret minimization. Different choices could therefore be driven by different choice paradigms. It is therefore important not just to compare the two models, but also to investigate when one model is better suited than the other for describing choice behaviour.

4.   Survey design and data description

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. We conducted two focus groups, one with kayakers from the university kayak club in Galway, Ireland, and a second one with 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. The site 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, and, as rightly pointed out by an anonymous reviewer, also creates potential problems of endogeneity, in the sense that alternatives with high utility are likely to have high crowding due to high frequency of visits, 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. The data collection took place in January 2004. 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 meeting on the Liffey River. A total of 315 surveys were sent 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, 42 from the on-site survey, and the remaining 35 from questionnaires downloaded from the website) obtaining an unbalanced panel with 3,466 usable choices. In terms of characteristics of the sample, the majority of respondents were male (78%); 70% of the sample was single, and 13% of those interviewed had children. The mean income 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 6 months and a maximum of thirty-six years, with the mean equal to 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.

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. More specifically, the Star quality rating for each river is taken from the Irish whitewater Guide Book, while other attributes are rated on a scale of 1 to 5, where 1 is poor and 5 is excellent. In case of "Crowding", 1 means very crowded and 5 means uncrowded.[13]

5.   Empirical comparison between RUM and RRM

Table 1 presents the results from the RU-MNL and the RR-MNL. Both models were estimated in Python Biogeme, a recent and more flexible development of the software

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[13] For a complete description of the survey, see Hynes et al (2007, 2008).

Biogeme (see Bierlaire, 2003, 2009). In the models, the dependent variable, whitewater site visit, takes on a value of 1 if a kayaker has made a trip to whitewater site i for each of the kayaking trip occasions taken in the previous twelve months, and zero otherwise.

[Table 1 about here.]

Overall, the RU-MNL provides a better fit for the data (the difference in model fit is found to be significant at the 1% level using the Ben-Akiva and Swait test). According to the RU-MNL, kayakers have a positive preference for the quality of car parking at the site, suggesting that better quality parking yields higher utility for kayakers. Similarly, crowding has a negative and statistically significant impact, which should be expected: the more congested a site is perceived to be, the more unpleasant the recreational experience may be. A higher star quality rating of the site translates into positive and significant utility for kayakers in the sample. Both water quality and scenic quality are significant; however, they appear to have a counterintuitive negative sign. This finding echoes results found by Hynes *et al* (2008) who suggest that water quality is not generally an important aspect of kayakers' choice, unless the level of water pollution is extreme. It is also worth noticing that sites such as the sluice on the Liffey and the Curragower wave on the Shannon are located either close or in large urban centres, where rivers tend to have less scenic value and more water quality problems. Despite these characteristics, these rivers are frequented by large numbers of kayakers, due to their proximity to where people work and live. It is also likely that rivers with good water quality and high scenic value may attract a large number of anglers. The latter may be seen by kayakers as competitors for the use of the rivers, hence kayakers may shy away from rivers that are popular among anglers. In general, the RU-MNL results

indicate that kayakers have a preference for information on water levels prior to visiting the site. This makes sense, given that there are costs associated with travelling to recreational sites, and kayakers wish to know the likelihood of having a good recreational experience prior to making their trip. Finally, the coefficient associated with the travel cost is negative and highly significant, as expected.

When comparing the two models output, both the RU-MNL and the RR-MNL find a similar level of statistical significance for the attributes of the study. We also notice that the coefficient estimates from the RR-MNL maintain the same signs as in the RU-MNL. However, as noticed in section 2, the interpretation of the coefficient estimates from the two models is not directly comparable. For example, the coefficient for the quality of parking is positive and significant, suggesting that regret increases as an improvement in the quality of parking at a non chosen alternative increases (compared to the quality of parking at the chosen alternative). On the other hand, the negative coefficient for the travel cost suggests that regret decreases as the difference in travel costs between a chosen and a non chosen alternative increases (because the non chosen alternative has become more expensive).

In addition to the interpretation of the parameter estimates, another interesting aspect of the RR-MNL is its capacity to better explain some choices, namely choices that follow a regret minimization approach. Therefore, to explore which choices are better explained by the RR-MNL, we report the result from a binary logit model to examine which attributes of the selected destinations and which respondents' characteristics are more likely to explain choices driven by utility maximization, rather than by regret minimization. Table 2 presents the results from this exploration. The dependent variable is equal to one if the RU-MNL outperforms the RR-MNL in terms of Log-likelihood at the choice level. The independent variables used in this model include the frequency of visits in the last twelve months to each

site, the self-reported skill level of the kayaker and ten whitewater sites which are estimated relative to the base site of the River Liffey, which flows through the centre of Dublin.

[Table 2 about here.]

Table 2 shows that for kayakers who have visited a particular site more often their choices are better described by utility maximization than regret minimization. This result is quite intuitive, since it suggests that the more frequently a kayaker visits a particular site, the less he/she will consider the performances of the sites that were not visited. On the other hand, when going to a site that the kayaker visits quite rarely, regret minimization performs better than utility maximization because he/she may be afraid that non-chosen sites may perform better than the chosen one, on one or more attributes. An alternative interpretation is that someone visiting a site less frequently, when choosing that site, he/she is likely to be attracted by the 'in-between' performance of the characteristics of that site compared to other sites that may have a poor performance on some attributes and a good performance on other attributes. In this case, the respondent would exhibit the compromise effect, which is captured by the RR-MNL and not by the RU-MNL.

As previously found by Hynes et al. (2007), the skill level of the kayaker also seems to have an important influence in the decision-making process of the kayaker. Advanced skill kayakers' behaviour would appear to be better described by regret minimization rather than by utility maximization. Basic skilled kayakers may not be as concerned about trading off features of the kayaking sites as they are probably just interested in maximizing their utility in terms of enjoying their kayaking experience. The logit model results also suggests that

advanced skilled kayakers try to minimize the regret of going to a site that may be worse in certain characteristics compared to other sites that were not chosen. The remaining variables in the model are site specific dummy variables, equal to one when a site is visited and zero otherwise. The reference dummy is the Liffey river, which flows through Dublin, and is the most frequented and well known river among kayakers in Ireland. The effect of the Liffey river is captured by the intercept, which is not statistically different from zero, suggesting that the choice of visiting the Liffey river appears to be driven both by regret minimization and by utility maximization. All other rivers are better described by regret minimization except the Roughty, the Dargle and the Boluisce – all quite popular rivers – which are better described by utility maximization.

Policy Impacts of site changes

Estimating the effects of changes in the quality or supply of environmental goods is an important objective of environmental valuation studies. In this section, we consider the implications of the choice between RU-MNL and RR-MNL approaches for two hypothetical changes in recreation quality. The hypothetical changes that we consider are (a) the introduction of a €5 parking fee per day at the river Liffey and (b) a situation whereby the Liffey becomes very crowded, which could easily happen given its location in the Dublin area. Table 3 reports the Logsum difference between the current situation and the two hypothetical scenarios.

[Table 3 about here.]

Introducing a parking fee at the access point to the Liffey produces a median and mean loss under the RU-MNL, as the expected maximum utility decreases for all respondents. Under the RR-MNL, the expected minimum regret increases for most respondents, but not for all. For at least one quarter of respondents, there is a decrease in regret. This can be justified by the fact that if the parking fee at the Liffey increases, for most kayakers their regret will increase because the Liffey is a popular site, but not for all. Indeed, there is a small group of kayakers whose regret has decreased. These are likely to be kayakers that already didn't find the Liffey very attractive before the hypothetical change, and after the hypothetical change, as the Liffey has become even less attractive, their regret decreases.

In the second hypothetical change in recreation quality, we consider a situation in which the Liffey becomes crowded. Under this hypothetical situation, the expected maximum utility decreases and the expected minimum regret increases. In this case, no kayaker is better off, considering both the RU-MNL and the RR-MNL. If we compare the median values of the Logsums, we find that under both models, the hypothetical change that negatively affects kayakers' experience the most is the one that introduces a €5 parking fee at the Liffey river. However, we stress that with the introduction of this parking fee, for some kayakers there is a reduction in the level of regret.

6.   Conclusions and discussion

This study compared the popular and widely used choice model, the Random Utility Maximization model to a new modelling approach, the Random Regret Minimization model that has been recently introduced in the transport choice literature. Our contribution to the literature is two-fold. First, this study represents the only application to date of the RR-MNL modelling approach to revealed preference data within the field of environmental and resource economics. Second, this study presents one of the first applications of the Logsum

based on RR-MNL to provide more information for assessing the welfare changes associated with different hypothetical quality changes.

Using data from kayakers' site choice in Ireland, we find that the RU-MNL model performs slightly better than the RR-MNL, although the difference is relatively small. We also find some illuminating factors that contribute to the RR-MNL's ability to describe choice behaviour more accurately, in some instances, than the RU-MNL. In the recreational site choice context that was considered in this study, we find that the more familiar a site is (denoted by the frequency of visits to a site for recreation), the more likely the choice of this site is better explained by utility maximization (RU-MNL) than regret minimization (RR-MNL). We also find that for many of the less familiar sites compared to the Liffey, the choice of these sites are better described by the RR-MNL than by the RU-MNL. This can have important management implications because it suggests that site managers may require different management strategies if they aim to increase kayakers' visits to specific sites. Also, intermediate and advanced skilled kayakers' choices would appear to be better described by regret minimization rather than utility maximization, reflecting the fact that this group of recreationists may give more consideration to the difference in the level of attributes between sites compared to their basic skilled level counterparts.

The analysis of the Logsum under hypothetical changes in recreation quality highlighted both similarities and differences in impacts arising from the two modelling approaches. Both models show that the increase in crowding at a site negatively impacts kayakers' experience. For all respondents under the RU-MNL the introduction of a parking fee reduces kayakers' utility. However, the RR-MNL is able to show that the introduction of a parking fee has some positive effects, as it decreases the regret for a quarter of kayakers.

Similar to previous studies that have applied both RU-MNL and RR-MNL, the two approaches retrieve similar model fits and estimate the same number of parameters. However, they do imply slightly different conclusions arising from the research. This begs the question about which modelling approach the researcher should apply. We would argue that, given the ease with which RR-MNL models can also be estimated using the standard econometric approaches, the analyst should consider applying both modelling approaches to their data. Moreover, the results from this study suggest that, since some choices are better described by utility maximization and some by regret minimization, then it may be prudent to apply the model that best reflects the particular choice behaviour. This approach would capture the behavioural influences on choices more accurately than assuming in all instances that individuals always make choices within a utility maximization framework.

Acknowledgements

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Table 1: Model estimates for RU-MNL and RR-MNL

	RUM		RRM	
Attribute	**Coeff**	**|t-stat|**	**Coeff**	**|t-stat|**
Quality of parking	0.070	3.36	0.012	3.27
Crowding	-0.088	4.37	-0.016	4.43
Star quality rating of the whitewater site	0.241	8.77	0.043	8.8
Water quality	-0.206	9.96	-0.036	9.4
Scenic quality	-0.073	3.23	-0.013	3.29
Availability of information on water levels prior to visiting the site	0.372	17.24	0.067	16.94
Travel Cost	-0.047	40.48	-0.009	38.59
Log-likelihood	-6,899		-6,929	
Rho2	0.167		0.165	
Observations	3,466		3,466	

Table 2: Logit model to explain determinants of RU-MNL outperforming RR-MNL; (3,466 observations).[†]

	Value	**t-stat**
Intercept	0.109	0.86
Frequency of visits to a particular site	0.035	16.81
Self-reported intermediate or advanced skill level (dummy variable)	-0.303	-3.67
Cliften Play Hole (dummy variable)	-1.797	-12.18
Curragower Wave (dummy variable)	-0.988	-7.11
The Boyne (dummy variable)	-0.382	-2.79
The Roughty (dummy variable)	0.709	2.97
The Clare Glens (dummy variable)	-1.426	-6.88
The Annemoe (dummy variable)	-1.687	-11.70
The Barrow (dummy variable)	-1.352	-5.93
The Dargle (dummy variable)	0.657	2.97
The Inny (dummy variable)	-2.510	-10.92
The Boluisce (dummy variable)	0.440	2.15

[†] The dependent variable is equal to 1 if RU-MNL outperforms RR-MNL, and 0 otherwise.

Table 3: Welfare change: Logsum differences between the current situation and after the implementation of hypothetical changes (a) and (b)

	(a) Introduction of a €5 parking fee at the Liffey river		(b) The Liffey becomes very crowded	
	RU-MNL	RR-MNL	RU-MNL	RR-MNL
1st Quarter	-0.047	-0.005	-0.036	0.000
Median	-0.025	0.005	-0.017	0.003
Mean	-0.032	0.011	-0.025	0.010
3rd Quarter	-0.014	0.024	-0.011	0.019