Congestion management in protected areas: Accounting for respondents' inattention and preference heterogeneity in stated choice data

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Abstract

Congestion levels in protected areas can be predicted by destination choice models estimated from choice data. There is growing evidence of subjects' inattention to attributes in choice experiments. We estimate an ANA Latent Class-Random Parameters model (LC-RPL) that jointly handles inattention and preference heterogeneity. We use data from a choice experiment designed to elicit visitors' preferences towards sustainable management of a protected area in the Italian Alps. Results show that the LC-RPL model produces improvements in model fit and reductions in the implied rate of inattention, as compared to traditional approaches. Implications of results for Park management authorities are discussed.

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1. Introduction

This paper explores the benefits of accounting for choice heuristic strategies when using destination choice models to inform management plans of protected areas in agriculturally marginal lands. One of the main challenges that managers of protected areas need to face is to pursue the goals of nature conservation, cost efficiency and income generation for local operators. While conservation is the *raison d'être* of protected areas, it is also true that tourism can generate income for local populations and contribute to the financial self-sufficiency of such agriculturally marginal areas. Indeed, because of the increasing dearth of public funds, the financial self-sufficiency of protected areas is crucial for their economic sustainability. On the other hand, the excessive human pressure that tourism may cause can lead to reductions in biodiversity and environmental quality of natural areas through litter, noise, and human access to fragile lands. It may also restrict economic land use options for farmers. Developing effective management plans can therefore be extremely challenging for the local authorities in charge of protected areas. Furthermore, visitors of protected areas tend to have well differentiated needs and preferences, which are often difficult to reconcile across interest groups. For this reason, an improved understanding of the recreational demand is crucial to develop management plans aimed at attracting visitors while preserving nature and satisfying the expectation of local residents whose income is derived in part by forestry and grazing.

Over the past decades, destination choice models based on choice experiment (CE) data have become a popular method to model preferences for outdoor recreation. Such approach has been applied in different recreational environments, such as beaches/seas (Wielgus et al., 2009, Matthews et al., 2018), lakes (Smirnov and Egan, 2012), forests (Juutinen et al., 2014; Oviedo et al., 2016) and mountains (Sælen and Ericson, 2013). Among CE studies that focused on outdoor recreation in protected areas, there are Thiene et al. (2012) at Natural Park of the Regole D'Ampezzo (Italy), Juutinen et al. (2011) at Oulanka National Park (Finland), Chaminuka et al. (2012) at Kruger National Park (South Africa) and Jeanloz et al. (2016) at National Park Hoge Kempen (Belgium).

Some studies specifically addressed the issue of overcrowding in natural areas. Kohlhardt et al. (2017) investigated visitors' preferences for attributes of Garibaldi Provincial Park in British Columbia (Canada) and found that overcrowding negatively affects utility associated with visits, especially when it occours in location with access to exceptional viewscapes. Thiene et al. (2017) also found evidence of negative effects from increasing number of people encountered while trekking on trails in the Dolomiti Bellunesi National Park (Italy). Results from the study of Leon et al. (2015) at national Park of Rosario and San Bernardo (Colombia) showed that tourists have different preferences for recreation sites according to the level of congestion.

The methodology behind CE is rapidly evolving and substantial progress has been made in recent years in terms of both experimental design and data analysis. As part of these developments much effort has been devoted to studying the use of choice heuristics, or simplified decision rules used by respondents, whose choice behaviours do not align with standard model assumptions. One of the heuristics that have been identified in the literature is the tendency to ignore one or more of the attributes describing alternatives during their evaluation, a phenomenon that has been labelled attribute non-attendance (ANA). Following the contribution by Hensher et al. (2005) several papers have reported evidence of ANA in a variety of fields including transportation (Hensher, 2006; Hensher and Greene, 2010; Collins 2012), environmental valuation (Campbell et al., 2008; Scarpa et al.; 2009; Carlsson et al., 2010; Balcombe et al., 2011; Kragt, 2013), food choice (Kaye-Blake, et al. 2009; Caputo et al. 2013) and health economics (Ryan et al., 2009; Hole, 2011). There is also growing evidence that, when ignored, attribute non-attendance may lead to biased coefficient estimates, and hence biased estimates of willingness to pay (Scarpa et al., 2009; Hensher and Greene, 2010; Hole, 2011; Kravchenko 2014). Various methods have been proposed in the literature for identifying attribute non-attendance. One approach is to directly ask survey respondents whether they ignored any of the attributes when making their choices (Stated ANA). Another approach is to use econometrics to estimate the probability of attribute non-attendance directly from choice patterns (Inferred ANA). The type of model used for this has typically been an Equality-Constrained Latent Class model, where the classes, rather than latent preference groups, represent different attribute processing strategies and during estimation parameters are set to zero in specific classes to account for ignored attributes (Scarpa et al., 2009, Hensher and Greene, 2010; Campbell et al., 2011), while they are constrained to be equal across classes when non zero. As noted by Hess et al. (2013), this approach might produce misleading results because while accounting for non-attendance it ignores taste heterogeneity. For his reason, some recent studies advocated the adoption of choice models that simultaneously account for ANA and latent taste heterogeneity (e.g. Hensher et al., 2013; Hess et al., 2013; Collins 2012; Collins et al., 2013; Caputo et al. 2013). Such studies found this approach to improve model performance and to retrieve lower ANA rates and a more accurate description of respondents' choice behaviour, which ultimately ought to generate superior policy recommendations.

Despite its advantages, to the best of our knowledge this approach has never been applied in empirical studies on outdoor recreation in natural areas. Investigating ANA in such context is particularly relevant in the light of the many activities visitors practice in conservation and recreation areas and the respective visitors' categories. It is quite plausible that in deliberating destination choice visitors interested in practicing a specific activity assign more weight to attributes directly affecting the activities of interest and might completely ignore others. This would lead to incomplete trade-offs and non-compensatory choice, thereby violating basic choice model assumptions. For examples, visitors only interested in picnicking may ignore attributes related to hiking trails, or visitors only interested in training (e.g. mountain bikers) may ignore attributes related to park biodiversity.

To tackle these issues, we estimate destination choice models on data retrieved from a CE focused on visitors' preferences for park attributes at National Park Dolomiti Bellunesi, a protected area in the North-East of Italy. In our modelling approach, we overlay to the attribute non-attendance classes, which is a choice behaviour process, a preference heterogeneity process. The latter is based on assumptions of continuous distributions of random parameters within each non-attendance class and independent across classes. In other words, we estimate an ANA Latent Class-Random Parameters model (LC-RPL) that simultaneously accounts for both ANA and preference heterogeneity.

To explore the benefits of accounting for both ANA and preference in outdoor recreation studies, we use the estimates of the econometric model to simulate outcomes for two policy scenarios. These involve changing the provision of picnicking facilities in the park. In particular, we analysed the shift of visit probability in the seven top park destinations: Passo Croce d'Aune, Val di Lamen, Val di Canzoi, Val del Mis, Candaten, Val Cordevole and Val dell'Ardo. We focused on changes in picnicking facilities because of the popularity of such activity within the park. From the management view point it is also one of the most impactful in terms of both environmental and economic implications. Some of the main picnicking destinations, such as Val del Mis, report large numbers of visitors and are experiencing periodical overcrowding. Predicting the change in visits distribution caused by specific policy measures can be a crucial tool to help park authorities to develop management plans aimed at alleviating pressure on the environment at congested sites.

This paper contributes to the literature in two ways. First, it explores the advantages of adopting LC-RPL models to investigate both ANA and taste heterogeneity in empirical applications on outdoor recreation. To the best of our knowledge, it is the first study to do so. Second, it investigates the potential of such approach in terms of informing policies aimed at reducing overcrowding and congestion issues in recreational sites.

The remainder of the paper is organized as follows: section 2 illustrates ANA in detail and reviews previous studies on this field; section 3 outlines the econometric model adopted in the study; section 4 describes data collection; section 5 reports the results of our study whereas section 6 presents the conclusions.

2. Attention to destination attributes

CE is based on the economic theory of consumer behaviour (Lancaster, 1966; McFadden, 1974), which posits various axioms about individuals' preferences, amongst which that these are complete, monotonic, transitive and continuous. Continuity of preferences implies that individuals use fully compensatory in their decision-making processes. Typically, in a CE, this implies that respondents make trade-offs between the levels of each attribute to choose their preferred alternative. However, attention is costly, and in practice respondents may often lack the incentives and/or the cognitive resources to optimize their decision and to formulate accurate judgments based on tradeoffs across all proposed attributes (Cameron and DeShazo, 2010). For this reason, it has been argued that respondents behave in a rationally adaptive manner by seeking to minimize cognitive cost of choice and maximize benefit while making choices (DeShazo and Fermo, 2004). Respondents may therefore employ various attribute processing heuristics when making choices. Heuristics are strategies that consists in processing the available information with the goal of making decisions less cognitively costly, more quickly, frugally, and/or accurately than what is implied by more complex methods (Gigerenzer and Gaissmaier, 2011). If heuristic strategies are adopted, failing to account for them is likely to lead to misguided inference, as the econometric models used to analyze choice may not reflect the actual choice behaviour (Campbell et al., 2014).

The adoption of heuristic strategies often results in respondents choosing as if they were systematically ignoring one or more attributes, a phenomenon called attribute non-attendance (ANA). The collection of statistical evidence coherent with ANA has been carried out with different methods in the literature. Two common approaches are *stated* ANA and *inferred* ANA (Hensher, 2006; Scarpa et al., 2009; Scarpa et al., 2010). Stated ANA involves asking respondents specific follow-up questions to identify the attributes that they ignored when choosing, while inferred ANA refers to analytical models that "infer" from the observed pattern of choices.

Stated ANA is the first that has been used in the literature (Hensher et al., 2005) and can be further divided in two variants: *serial* ANA and *choice task* ANA. In the serial ANA, respondents are asked at the end of the sequence of choice tasks to report what attribute they feel they systematically ignored when choosing their preferred alternative. Instead, in the choice task ANA, such question is asked after each choice task.

The answers to these questions are usually used to inform the correct utility specification of discrete choice models. A common approach, described in Hensher et al. (2005) and then adopted by others (Hensher et al., 2007; Kaye-Blake et al., 2009; Kragt, 2013; Khelbacher et al., 2013) is to specify random parameter logit models in which the coefficient of attributes that respondents state to have ignored is constrained to zero. Such zero-constrained coefficients have been used by Campbell et al. (2008) who implemented them into an error component models with heteroskedastic errors for subsets of respondents that ignored different numbers of attributes. Similar zero-constraints were used by Scarpa et al. (2010), who adopted a heteroskedastic MNL accounting for error variance induced by design-related factors and ANA (both at the serial and choice task level).

It has been argued that respondents may state to have ignored an attribute even when they actually only assigned low importance to it (Hess et al., 2013). To overcome this issue, some studies opted to reduce the magnitude of ignored coefficients by means of shrinking parameters, instead of constraining them to zero (Hess and Hensher, 2010; Alemu et al., 2013; Kelbacher et al., 2013; Balcombe et al., 2014; Balcombe et al., 2015; Chalak et al., 2016). Such parameters are usually specified as having a continuous distribution in the interval [0,1] to relax the assumption that the non-attendance implies zero marginal utility (Carlsson et al., 2010; Balcombe et al., 2015). Another approach is based on separate estimations of attributes coefficients for respondents who reported complete attendance and for those who stated some form of ANA (Hess and Hensher, 2010; Scarpa et al., 2013).

Campbell and Lorimer (2009) questioned whether respondents' statements are reliable, as respondents may not answer follow-up questions truthfully for several reasons, such as social pressure to either care about specific attributes (especially in face-to-face interviews), or to consider all attributes as relevant (Balcombe et al., 2011). Another issue with using respondents' statements is potential endogeneity bias that arises from conditioning a model on self-reported ANA (Hess and Hensher, 2012). In several studies it was proposed the inferred approach as an alternative method to account for ANA (Scarpa et al., 2009; Hensher and Greene 2010; Hess and Hensher 2010). This method statistically infers ANA behaviour through the estimation of analytical models from observed choices. ANA is typically inferred by means of (behavioural) latent class models in which classes reflect different processing strategies (Hensher et al., 2012; Caputo et al.; 2013; Lagarde, 2013; Glenk et al*.,* 2015*;* Thiene et al., 2015; Hole et al., 2016; Caputo et al. 2017). Typically, such models include: *i*) a class in which all coefficients are constrained to zero, to which are likely to belong those individuals who ignored every attribute, therefore making random choices; *ii*) a class in which all coefficients are estimated, to which are likely to belong those who attended every attribute; *iii*) different combination of classes in which one or more potentially less relevant attributes are constrained to zero. Non-zero coefficients (that are those for attributes that have been attended to) are assumed to take the same values across classes (Scarpa et al., 2009; Hensher and Greene, 2010; Campbell et al., 2011; Hess et al., 2013). However, while practical this restriction is undesirable as it implies that all respondents are preference clones, because it ignores heterogeneity across people. Some applications (Caputo et al. 2013; Thiene et al. 2015) overcome this by mixing ANA classes with preference classes.

A more flexible form inspired by the combination of latent classes with continuous random parameters (LC-RPL) originally proposed by Bujosa et al. (2010) was extended to choice models with ANA by Collins (2012), and later adopted by others (Collins et al. 2013; Hess et al., 2013; Hensher et al., 2013). We also adopt an ANA LC-RPL specification to account for both attribute non-attendance and continuous taste heterogeneity. All studies based on models mixing preference variation with ANA classes found that ANA rates are substantially reduced, thereby suggesting that ANA can be (at least partially) confounded with taste heterogeneity.

Another method to infer ANA was proposed by Hess and Hensher (2010) (see also Scarpa et. al, 2013) and it is based on the estimation of the individual posterior conditional distributions of coefficients from a mixed logit model. In particular, they retrieved the individual-specific means (μ) and variances (σ) of random coefficient distributions to compute coefficients of variation (the ratio between σ/μ). High ratios (e.g. larger than 2) suggest large variability of the specific taste parameter and a high likelihood of inattention to the specific attribute by that respondent.

The inferred approach has been also applied to investigate the influence of individuals' characteristics on ANA probabilities. For example, Balbontin et al. (2017) related ANA to individuals' risk attitudes, whereas Sandorf et al. (2017) investigated the influence of knowledge about an attribute on probability to attend it.

Several studies employed both the stated non-attendance and the inferred non-attendance approach (Hensher et al., 2007; Hensher and Rose, 2009; Campbell et al., 2011; Scarpa et al., 2013). The overall finding is that results from inferred and stated ANA are inconsistent with each other, and that the inferred approach generally provides a better model fit.

Finally, the so-called *revealed* ANA involves detecting ANA by forcing the respondent to access information to attributes through various means (e.g. mouse movements and clicks in Kaye-Blake, 2006 and Kravchenko, 2016) or by means of eye-tracking technologies, which monitor the fixations and time spent on each attribute (Balcombe et al., 2015; Spinks and Mortimer, 2015; Balcombe et al., 2016; Chavez et al., 2016). This approach has the advantage of retrieving information without eliciting them from respondents, providing a less biased measure than that retrieved from stated ANA (Balcombe et al., 2015). Data retrieved by using this approach are usually modelled as in stated ANA approach, that is by estimating parameters that shrink the coefficients for attributes non-attended (Balcombe et al., 2015; Chavez et al., 2016). These studies found inconsistencies between stated and revealed ANA and that models informed with both approaches had the best results in terms of statistical fit. Importantly for serial ANA, Scarpa et al. (2010) and Spinks and Mortimer (2015) report evidence showing that the number of attributes ignored by each respondent can vary among choice tasks, thereby explaining differences between choice task and serial non-attendance.

3. The econometric model

In CE, probability selection of alternative i at choice task t is modelled using Random Utility Theory (Luce, 1959; McFadden, 1974) and the logit probability. Respondent n facing a set of J mutually exclusive alternatives denoted by j=1,…,J, and belonging to ANA class c, has utility from alternative i as a function of K attributes. Utility functions are assumed to be composed of a systematic part V_{ni}, dependent on researcher-observables, and of a random part ε_i standing for researcher-unobserved utility:

$$U_{itn|c} = V_{itn|c} + \varepsilon_i = \boldsymbol{\beta}_{nc}{}'\mathbf{x}_{it} + \varepsilon_i \quad \forall\, i \text{ in } J, \quad t = 1,2,\dots,T \quad n = 1,2,\dots,N \quad c = 1,2,\dots,C \qquad (1)$$

For ANA classes specific values of β_{tnc} are zero-constrained. If the unobserved error term ε_i is assumed to be i.i.d. extreme value type I, the conditional probability of individual n choosing alternative i out of J alternatives is logit:

$$Prob\left(U_i > U_j, \forall J | c, \boldsymbol{\beta}_{nc}\right) = \pi_{nti|c,\beta_{nc}} = \frac{\exp(\boldsymbol{\beta}_{nc}{}'\mathbf{x}_{it})}{\sum_{j=1}^{J}\exp(\boldsymbol{\beta}_{nc}{}'\mathbf{x}_{jt})} \qquad (2)$$

This is the choice probability conditional on belonging to ANA class c and random coefficient values $\boldsymbol{\beta}_{nc}$, which are each distributed according to parametric densities with location and scale parameters to be estimated, and are also class-specific.

Following Bujosa et al., (2010) and Greene and Hensher, (2013) we derive the unconditional choice probabilities by integrating over both finite mixing of latent classes probabilities as well as parametric densities for $\boldsymbol{\beta}_{nc}$.

To specify the membership probability to each latent ANA class, we adopt a semi-parametric form based on a class-specific constant term α (Scarpa and Thiene, 2005), where for class 1 such term is set to zero for identification. Using a Logit formulation for the class allocation model, the probability that individual n belongs to segment C is given by:

$$\pi_{nc} = \frac{\exp(\boldsymbol{\alpha}_c)}{\sum_{c=2}^{c=C} \exp(\boldsymbol{\alpha}_c)}, \text{ where } \alpha_{c=1} = 0, \text{ for identification purposes.} \tag{3}$$

Respondents preferences $\boldsymbol{\beta}_{nc}$ vary continuously within each class with class specific hyper-parameters (e.g. mean $\boldsymbol{\mu}_c$ and st. dev. $\boldsymbol{\sigma}_c$), which need estimation. The model simultaneously derives ANA class probabilities for respondents conditional on individual characteristics and estimates the distributional features of random utility parameters within each class which account for preference heterogeneity.

Integrating out within-class variation of preferences is obtained by:

$$\pi_{nti|c} = \int \prod_{t=1}^{t=T} \frac{\exp(\beta'_{nc}\mathbf{x}_{ti})}{\sum_{j=1}^{j=J} \exp(\beta'_{nc}\mathbf{x}_{tj})} f(\beta_{nc}) d\beta_{nc} \tag{4}$$

where random parameters follow a separate distributional law in each class and their random behaviour in class *c* is regulated by $\boldsymbol{\mu}_c$ and $\boldsymbol{\sigma}_c$ (Train, 1998; McFadden and Train, 2000). Finally, the LC-RPL unconditional probability that individual *n* chooses the *t* sequences of *i* in their choice task sequence can be written from equations (3) and (4) integrating out behavioural ANA classes as:

$$\pi_{nti} = \sum_{c=1}^{c=C} \pi_{nc}\pi_{nti|c} \tag{5}$$

Therefore, the sample log-likelihood reduces to:

$$LL = \sum_{n=1}^{N} \ln[\pi_{nti}] \tag{6}$$

Estimation involves the evaluation of a multiple-dimensional integral in (4) that has no close-form. So, in estimation this model requires approximation of (4) by numerical methods (Bhat, 1998; Revelt and Train, 1998).

Post estimation, the attributes' coefficients retrieved from the LC-RPL model were then used to simulate the change in destination choice probability to the seven main sites of the park (Passo Croce d'Aune, Val di Lamen, Val di Canzoi, Val del Mis, Candaten, Val Cordevole and Val dell'Ardo) under two hypothetical policy scenarios. The first scenario involved the introduction of an additional picnic area in Val di Lamen, whereas the second scenario focused on removing one picnic site from Val del Mis. Choice probabilities of each site were computed by including in the utility functions retrieved from the econometric model the actual attribute levels for each site, based on current park state.

4. **Park features and stated choice data collection**

In this paper, we explore visitors' preferences towards the implementation of sustainable management policies at Dolomiti Bellunesi National Park. The park, established in April 1990, is located in the North-eastern Italian Alps, covers 32,000 hectares and is the only nationally protected area of the region. Since 2009 it has been a UNESCO World Heritage site due to its biodiversity and to the remains of ancient human activities, which include several prehistoric archaeological sites, the mining centre of Valle Imperina, boasting over half a millennium of history, the Carthusian monastery of Vedana, the little churches of the piedmont area, the ancient medieval hospices of Val Cordevole, military roads, shepherds' huts, and all the so-called "minor" signs of the ancient life of man in the mountains.

One of the main features of the park is its outstanding landscape and its flora, which consists of about 1400 species, among which are many species deserving of mention, either because they are endemic, rare, or have great phytogeographical value. The presence of rare species and exceptionally high variety of environments is due primarily to the geographic location of the park. It lies on the South-eastern margin of the Alps in very inaccessible areas, some of which have remained ice-free during the last glaciation (10,000 to 12,000 years ago).

The park is also habitat to 42 species of mammals, 14 of which are included in the annexes of the EU Habitat Directive and therefore object of special protection. Among carnivores, bear, lynx and wolf are present in the park, which are very rare species in Italy.

Data were collected during summer 2013 during face to face interviews. A pilot study was conducted in June 2013 to calibrate the questionnaire. Upon the request of the park's management authorities, respondents were randomly selected within three categories of visitors, based on their main activity practiced during the day of the interview. These groups were: hikers, mountain-bikers and visitors who engaged in short-walks and/or pic-nicking. A final sample of 432 respondents completed the survey. To ensure a fully balanced design 144 respondents were interviewed for each of the three groups.

The attributes and levels were defined in agreement with the park's management, who was interested in collecting information about a specific subset of services. The CE consisted of ten attributes, whose levels are reported and described in Table 1.

The first attribute deals with bivouacs, which are facilities similar to alpine shelters located at high altitude in order to provide refuge to visitors in case of bad weather conditions. Currently, they can be accessed by visitors only upon request of the keys (baseline). The proposed service improvement is that they be always open and supplied with food and firewood. The second attribute focused on information centers. Currently there are two information centers, but the park was interested in investigating preferences for the creation of either two or five additional centers. The third attribute deals with the access to two of the main sites of the park: Val Canzoi and Val del Mis. These sites receive a large number of visitors, so the park authority is interested in exploring how to best manage car access. The baseline is that access to be always open, whereas the other two levels are either denying car access on Sundays or on both Saturdays and Sundays. The fourth attribute is related to congestion. The levels are: encountering less than 20 people, between 20 and 40, and more than 40 people. The fifth attribute focuses on the number of picnic areas. Currently there are 30 picnic areas, the two improvement levels propose to build 10 and 20 new dedicated areas, respectively. The sixth attribute concerns the reintroduction of the griffon vulture, a large bird iconic species which used to live in the park habitat. The seventh attribute concerns the timing of access to information centers. Currently, such facilities are open only during weekends, and the option of opening in the mornings of weekdays was explored. In addition, the last level proposed information centers being open two afternoons during weekdays as well. Thematic itineraries specifically focus on flora, fauna, cultural and historical aspects are one of the main attractions of the park. There are eight thematic itineraries and the service improvement included in the CE are to introduce additional eight or sixteen itineraries. Mountain-bikers are an important part of the tourism that interests the park, although no dedicated trails or services are available to them. As such, the park is interested in evaluating the creation of 2 or 5 mountain-bike itineraries. Currently, there is no entrance-fee to access the park. However, due to the decrease of public funding, the park authority is interested in evaluating its introduction. The selected levels for the cost of access attribute are €2, €5, €7, and €10.

All the attributes, with the exception of the first (bivouacs) were numerically coded for the purpose of the analysis. The levels relating to the second and seventh attributes (access to the valleys and information centers opening) were expressed in terms of days and hours, respectively.

The experimental design is characterized by four different waves for each of the three groups of visitors. Two attributes are excluded at the end of each wave based on the results retrieved from a basic MNL model estimated on collected data. MNL results are used as priors for the derivation of a WTP_b-efficient design (where subscript b denotes Bayesian priors, Scarpa and Rose, 2008) for the subsequent waves (Ferrini and Scarpa, 2007; Vermeulen et al. 2010). In each subsequent wave, the attributes with significant coefficients or less relevant for specific group of visitors (for example bivouacs for mountain-bikers) were excluded from further investigations. The aim of the strategy was to evaluate least accurate parameter estimates with a larger sample size. Samples in later waves could dedicate more attention to attribute evaluation as they were progressively presented with fewer attributes. The survey for the first wave included all ten attributes and was the same across all groups of visitors. The second wave had eight attributes, the third six and the last one four. The cost attribute was included in every wave and four each group. Within each sample group and each wave 36 visitors were surveyed and each of them was presented with 12 choice tasks for an overall balanced sample of 432 completed surveys. In the first wave the efficient design consisted of 72 choice tasks that were blocked into six groups, in the second wave there were 36 choice tasks blocked into three, the third one had 24 choice tasks blocked into two and the last one had only 12 choice tasks.

ANA probabilities might depend on the number and type of attributes included in the experimental designs of the various waves and categories of respondents. To explore this dependency, we regress posterior class membership probabilities π_{nc}^{P}, retrieved from the LC-RPL model, upon experimental design features $\boldsymbol{d}_n$. For each class, the regression takes the form:

$$\pi_{nc}^{P} = g_c(\boldsymbol{\phi}, \boldsymbol{d}_n) + v_{nc} \tag{7}$$

where g_c is a linear addictive function, $\boldsymbol{\phi}$ is a vector of coefficients and v_{nc} is the error term. As probabilities π_{nc}^{P} are jointly determined, the regressions outlined in equation (7) need to be considered as a system and its coefficients simultaneously estimated.[1]

Given that π_{nc}^{P} for each class is bounded in (0,1) and $\sum_c \pi_{nc}^{P} = 1$, we follow Wu et al. (2004) and assume that probabilities π_{nc}^{P} follow a Dirichlet distribution. The log-likelihood function of the Dirichlet regression[1] is expressed as (Woodland, 1979):

$$LL_n = ln\,\Gamma(H) - \sum_{c=1}^{C} ln\,\Gamma[Hg_c(\cdot)] + \sum_{c=1}^{C} ln\,\Gamma[Hg_c(\cdot) - 1]\; ln\,(\pi_{nc}^{P}) \tag{8}$$

where H is a constant and $\Gamma(\cdot)$ is the gamma function.

The experimental design features (that are the elements of $\boldsymbol{d}_n$) included in the analysis are the sequential waves and visitors' category. In our design the number of attributes varies across different waves. So, this approach allows us to investigate the effect of design features on posterior ANA probabilities. This is of interest as previous studies retrieved mixed results. For example, Hensher (2006), Hensher et al. (2012) and Collins and Hensher (2015) found that the number of attributes influences ANA probabilities, whereas Weller et al. (2014) found no evidence of such effect. By including in the analysis visitors' category, we can account for respondents not seeing

[1] We also estimated fractional logit models (Papke and Wooldridge,1996) on posterior probabilities for each class. The results are consistent with those retrieved from the Dirichlet regression and are available from authors upon request

certain attributes in their choice sets. We expect such visitors to have a higher probability to exhibit a behaviour consistent with ANA for those attributes, compared to other respondents.

5. Results

Accounting for all possible ANA patterns requires the estimation of an LC-RPL model with 2^k classes, where k is the number of attributes included in the CE. In our case, as the attributes are 10, this would lead to a model with $2^{10} = 1024$ classes, whose estimation is unfeasible. As such, we adopted a stepwise approach to identify the model that more accurately describes the decision strategy of our target population. We note that this approach is common in the ANA literature. For example, Scarpa et al. (2009) report LC ANA models with 9 to 13 classes, out of the possible 27 ANA combinations, as they found that models with higher number of classes did not significantly improve data fit. Similarly, Lagarde et al. (2012) report results from a model including only 10 of the 64 possible ANA patterns. Campbell et al. (2012) adopt a LC model in which each class describes ANA for only one attribute, as they found that including classes with two or three at a time attributes ignored did not improve data fit.

The starting model of our stepwise approach is a LC-RPL model with 12 classes, of which one ANA class for each of the attributes (each class with one single coefficient set to zero), one for the total attendance decision rule (i.e. none of the attribute coefficients set to zero) and one for total nonattendance (i.e. all attribute coefficients set to zero). We estimated such model using different type of draws (Halton and MLHS), number of draws (from 100 to 5000) and starting values (retrieved from the estimation of MNL, RPL and LC models). However, in all cases we found this model specification to cause estimation issues and to produce class sizes unreasonably small and with several insignificant coefficients. For these reasons, we moved to more parsimonious specifications, focusing on those attributes that seem more likely to be ignored. Table 2 reports log-likelihood values for the estimated models, as well as values for AIC and BIC, which were computed to enable comparison across specifications and number of parameters. The base specification uses three classes, one for total attendance, one for total ANA and the last for ANA for the cost attribute, which is quite relevant given its implications on the computation of WTP values. According to all information criteria considered, this model specification substantially outperforms the traditional MNL model, providing evidence of the existence of both ANA for the cost attribute and preference heterogeneity across the individuals of our sample.

To further refine the model by including other potential non-attendance classes, we proceeded by estimating nine 4 class specifications, each adding in turn one ANA class with non attended attribute. As shown in Table 2, the best performing model specifications are those with an additional class for ANA for the reintroduction of the griffon vulture and ANA for number of information centers. For this reason, we move to a specification that involves five classes: for total attendance, for cost, for ANA for griffon vulture reintroduction, for number of information centers and one for total ANA (e.g. random choice). In the final step we tried in turn to add a second non-attended attribute from the list of the seven attributes left out. These were added to each of the non-attendance classes in the base model with five classes. Using the above procedure, the best-performing specification is the one with the following five classes: i) total attendance, ii) total ANA, iii) ANA for cost, iv) ANA for griffon vulture reintroduction, v) ANA for number of information centers and their opening hours. In all of the above the picnic areas and the cost coefficients for class 3 were kept non-random to allow identification of the marginal rates of substitution. In our final model all coefficients are assumed to be random, besides those associated with picnic areas in all classes and cost in class 3, which are fixed. We assumed that all random coefficients follow a normal distribution, apart from the coefficient for cost which, in class 1, follows a log-normal distribution.

To compare the LC-RPL to the traditional LC approach, we estimate the model with five classes in both specifications. According to all information criteria, the LC-RPL outperforms the LC one. Table 3 reports the estimates of the non-attendance shares retrieved from the both specifications. Similarly to the results reported by Hess et al. (2013), non-attendance rates retrieved with the LC-

RPL specification are consistently lower than those implied by the LC specification. In particular, the LC-RPL estimated probability of membership to the class associated with attendance to all attributes is 72.2% while the LC estimate is 50.6%. This seems to confirm previous findings of overestimation of the non-attendance rate from the traditional LC model specification. ANA probability estimates for the cost attribute move from 16.0% to 8.0% when preference heterogeneity within ANA latent classes is allowed for; for the griffon vulture reintroduction, the probability estimates reduce from 13.2% to 7.9%; for information centers and opening hours from 13.9% to 7.0%. Instead, the estimates for total non-attendance (i.e. ignoring all attributes, or equivalently assigning random choice to alternatives) increase from 4.9% in the LC-RPL model to 6.3% in the LC.

Table 4 reports coefficient estimates for both models. To be able to compare the estimated values of utility coefficients across classes, we report marginal rates of substitution with the coefficient for picnic areas (MRS/pic). We choose this measure instead of the common choice of using WTP because the latter cannot be computable in non-attendance class 2, in which such coefficient is ignored and constrained to zero.

In the LC-RPL model most of the standard deviation estimates are significant at 90% in each class, which confirms our hypothesis that respondents' preferences are heterogeneous within each attendance class. Moving to the analysis of the number of significant estimates for the means of random attribute coefficients in each class, as expected the cost estimate is significant and negative in all classes in which it is attended to, and in both specifications. The alternative-specific constant for the status-quo is also significant and negative in each class. This suggests that respondents are generally willing to improve the current recreational offer provided by the park. The estimate for congestion is also negative and significant across classes and models, with the exception of class 4 in the LC specification. Overall, the LC-RPL model implies a higher number of significant mean coefficient estimates than the LC one, which confirms the improvement of model performance achieved by introducing preference heterogeneity in the model.

Moving to the analysis of estimated parameters in each class, the total attendance class is the one with the highest number of significant **β** parameters in both models (ten out of eleven in the LC-RPL and nine out of eleven for the LC). Importantly, the coefficient for the reintroduction of the iconic griffon vulture is positive and statistically significant in the LC-RPL model, but insignificant in the LC one. Along with the higher rate of ANA for this attribute estimate in the LC model, this result suggests that ignoring preference heterogeneity in LC models might lead to a substantial underestimation of the benefits deriving from reintroducing the griffon vulture in the park territory. Moving to class 2 - which implies ANA for cost - it is interesting to note that according to the results of the LC-RPL model, respondents in this class seem to be the most willing to improve current service levels. This is suggested by the value of the status quo ASC, which is the lowest among all classes (MRS/pic = -23.04). It seems plausible that visitors with the highest interest in the improvement of park services are those whose choice behaviour is least affected by cost levels. In the LC model, instead, the status-quo coefficient estimate is lowest in classes 3 and 4. As for reintroduction of griffon vulture in class 1, in class 2 the coefficient estimate for the number of information centers is positive and significant only in the LC-RPL. Again, this suggests that the LC model underestimates the benefits of the improvement of this service. It is interesting to note that in class 3 - which implies ANA for griffon vulture reintroduction - respondents strongly favour mountain biking trails. It is reasonable that those who are interested in activities that are not strictly linked to the natural aspects of the park (e.g. mountain biking) would not benefit from the griffon vulture reintroduction may indeed. This is also consistent with the negative value of the coefficient associated with number of thematic trails in the LC-RPL model. In Class 4 (ANA for information centres and opening hours) the LC-RPL model substantially outperformed the LC in terms of number of significant parameters (seven vs five). In particular, according to the LC-RPL model individuals in this class are interested in the provisioning of food and firewood in bivouacs and in the unregulated access to Val del Mis and Val Canzoi, whereas such attributes have no significant effect in the LC.

5.1 Effect of design features on ANA probabilities

Table 5 reports the presence/absence of attributes across the designs of the sequential waves of sampling and categories of visitors. The attribute gryphon reintroduction was excluded in waves 3 and 4 for hikers and mountain bikers, whereas number of information centres and their opening hours were only excluded for hikers in wave 4.

Table 6 reports the $\boldsymbol{\phi}$ coefficients estimated using a Dirichlet regression, which we use to explore the effects of experimental design features on posterior class membership probabilities. The Dirichlet regression was estimated in R 3.5.0 by using the package DirichletReg (Maier, 2014). The effects of sampling waves are identified using wave 4 as a baseline, whereas those for visitors' category are to be interpreted as differences from those visitors traveling for picnics, which were used as a baseline.

Respondents from waves with largest number of attributes in the design (wave 1 and wave 2) have a negative and significant effect on probability of total attribute attendance behaviour (class 1). This supports the findings of Hensher (2006), Hensher (2012) and Collins and Hensher (2015) of a significant effect of number of attributes on ANA. As expected, wave 1 and wave 2 have also a negative effect on class membership probabilities for ANA for gryphon (class 3). That is, respondents who faced this attribute have a lower probability to exhibit behaviour consistent with having systematically ignored it than respondents who did not have this attribute in the design. It is also interesting to note that hikers and mountain bikers have higher and significant effect on the probabilities of belonging to the non-attendance class for the gryphon reintroduction than visitors engaged in picnic, which is the only category having always faced gryphon reintroduction attribute. Bikers and hikers are plausibly less interested in conservation initiatives of this type as they focus on other factors. Finally, wave 1 and wave 2 have a positive effect on the membership probability to belong to the total ANA class.

5.2 Choice simulations for policy scenarios

We explored changes in visitation probabilities in two policy scenarios by using both LC and LC-RPL estimates. In the first scenario, an additional picnic area would be introduced in Val di Lamen, a site which is currently interested by a relatively small number of visitors. In the second scenario, a picnic area would be removed from Val del Mis, which is one of the most congested sites in the park area. As expected, in the first scenario the inferred probability of visit for Val di Lamen increases, as shown in Figure 1, which reports the change in percent probability of visit in the presence of the improvement. The simulation on LC-RPL estimates shows a higher shift in probability (about 4.5%) that the LC one (nearly 3%). Both models predict highest decreases in visitation probabilities for Val Canzoi, Val del Mis and Candaten, which are sites with picnic facilities. Interestingly, the simulation from LC-RPL estimates shows a substantial decrease in visitation probability for Val Canzoi, which is one of the sites interested by overcrowding issues. Overall, the simulations suggest that increasing the offer of picnic areas in Val di Lamen could be an effective policy measure to reduce the overcrowding in congested sites, such as Val del Mis and Val Canzoi. By comparing simulations from the two models it is apparent that there are substantial differences in terms of the predicted magnitude of the policy effect in different sites. Ignoring latent preference heterogeneity in ANA destination models could therefore lead to inaccurate indications for managers of protected areas.

Figure 2 illustrates the shift in site choice probability following the second policy scenario involving the removal of picnic area in the highly congested Val del Mis. As expected, the inference suggests Val del Mis to be the site with highest visitation probability change (around -3% for both models). In this scenario, highest increase in visitation shares concerns Candaten, Val del Mis and Val di Lamen, which are sites that offer picnic facilities. Choice probabilities for hiking sites (Valle dell'Ardo, Val Cordevole and Passo Croce d'Aune) are only marginally affected. Interestingly, the simulation based on LC estimated predicts Candaten to be the site with the highest increase in visitation probability, whereas according to the LC-RPL based one Val Canzoi would be the most affected site. This suggest that adopting LC estimates to inform management plans would lead to an overestimation of the benefits of the intervention, as the LC-RPL predicts a substantial part of visitors to move from an overcrowded site to another with the same issues.

Overall, by comparing the two policy scenarios, it seems that removing one picnic area from Val del Mis would be more effective in reducing the overcrowding issue in this site, as its choice probability decrease is higher than the decrease in the first scenario. However, direct measures introduced by park management authorities in the past (such as limiting vehicular access to Val del Mis on weekends) were poorly received by visitors. As such, it seems that indirect measures, like improving the offer in other sites, could be a good compromise between reducing overcrowding (and therefore reducing the risk of environmental damages) and satisfying tourism demand.

6. Conclusions

We estimated a LC-RPL model that accounts for both non-attendance and preference heterogeneity using data from a CE investigating preferences of visitors of National Park Dolomiti Bellunesi for recreational services. In the face of the widespread use of behaviourally-based (rather than taste heterogeneity-based) latent class structures for capturing attribute non-attendance, this paper provides further evidence that the high rates of implied non-attendance usually retrieved with such models may be due, at least in part, to confounding non-attendance with preference heterogeneity. It also provides evidence that adopting LC-RPL models (i.e. combining discrete with continuous mixtures of preference) to investigate ANA in outdoor recreation studies can be a superior alternative to the adoption of traditional LC models. Allowing for variation of tastes within ANA classes improves model performance and more accurately describes actual choice behaviour. We also find substantial differences in between the two models in terms of predicting shifts in visitation probabilities as consequence of policy measures.

Our results confirm and extend those of previous studies (e.g. Hess et al., 2013; Collins et al., 2013) in that they seem to support the hypothesis that the widely adopted equality-constrained latent class specifications used to model attribute non-attendance may produce biased results. In particular, the results from the LC-RPL model suggest that the shares of attribute non-attendance classes are significantly lower when allowing for random heterogeneity within each class.

Our study also offers some insights on the effect of experimental design features on ANA probabilities. As others before us did, we also find that individuals are more likely to exhibit ANA behaviour when facing choice scenarios with high number of attributes. This further corroborates the importance of accounting for ANA in destination studies, as a large number of attributes is often required to accurately describe the wide array of services provided by recreational sites (e.g. eight attributes in De Valck et al., 2017; ten attributes in Thiene et al., 2012). While limiting the number of attributes may seem an obvious solution, it has some important shortcomings, most notably the risk of reducing the realism of the scenarios, by oversimplifying destination choices compared to those made in real life situations. As suggested by Hensher (2006), it may be preferable to limit ANA behaviour by ensuring the relevancy of the attributes. We tried to achieve this in our study by both defining the attributes according to park managers suggestions and by testing them in the field using a pilot study. The results offer some support to such measures, as the overall ANA rates we retrieved are quite low, despite the large number of attributes. With regards to the policy implications of our study, our results provide some guidance to the park management authorities. Firstly, it seems that a policy reintroducing the gryphon vulture (*Gyps fulvus*) and increasing the number of information centers are the two policy proposals least likely to benefit visitors. This is not only suggested by the relatively high share of respondents ignoring such attributes, but also by relatively low weight assigned to them by those who paid attention to them during the experiment. Other proposed measures, instead, such as the introduction of additional mountain biking and thematic trails, as well as the increase of the number of picnic areas, seem to be much appreciated by all visitors. Finally, the policy scenarios inferred from our preferred model allow us to draw some suggestions for the all important issue of congestion management. Our findings suggest that increasing the provision of picnic areas in sites that are currently less visited (e.g. Val di Lamen) may increase visitors' shares, thereby alleviating the pressure on the most congested ones. This represents timely guidance when one considers that past initiatives aimed at regulating visitors' access to the most popular sites (such as Val del Mis and Val Canzoi) were poorly received by visitors.

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Table 1: Attributes and levels

Attribute	Acronym	Levels
Bivouacs	bvc2	Bivouacs always open (dummy)
	bvc3	Bivouacs always open with facilities available (food, wood) (dummy)
Information centers	info	Number of information centers: currently 3 existing, building of 2 and 4 new information centers (3, 5, 7)
Vehicular Access	gst	Valleys always accessible, closed on Sunday but shuttle service, closed on Saturday & Sunday but shuttle service (7, 6, 5 days)
Crowding	cng	Number of people met: less than 10 visitors, 20-40 visitors, more than 40 visitors (0, 30, 80)
Picnic sites	pic	Number of picnic sites available: currently 30 existing, building of 10 and 20 new picnic sites (30, 40, 50)
Griffon vulture	grf	Reintroduction of Griffon vulture (dummy)
Open Information Centers	opn	Information centers open only during the week-end, during the week-end and all mornings, during the week-end and all mornings and during two afternoons (12, 27, 33 hours)
Thematic itineraries	itn	Thematic itineraries focusing on flora, fauna and historical aspects: currently 8 existing itineraries, building of 8 and 15 new thematic itineraries (8, 16, 23)
Trails for MTBike	mtb	Specific trails dedicated to mountain-biking: currently no MTB trails available, building of 2 and 5 dedicated trails for mountain-biking (0, 2, 5)
Entrance fee	cost	Entrance fee to access the park: currently no fee, introduction of 2€, 5€, 7€ and 10€ fee (0, 2, 5, 7, 10)

Table 2: Comparison of estimated models

Model	k	LogL	AIC	BIC
MNL	12	-4917.0	9857.9	9906.7
LC-RPL (COST)	32	-3970.5	8004.9	8135.1
LC-RPL (COST + BVC)	69	-3879.1	7896.2	8176.9
LC-RPL (COST + INFO)	69	-3826.1	7790.2	8070.9
LC-RPL (COST + GST)	69	-3860.3	7858.6	8139.4
LC-RPL (COST + PIC)	69	-3885.8	7909.6	8190.3
LC-RPL (COST + GRF)	69	-3815.7	7769.3	8050.0
LC-RPL (COST + OPN)	69	-3870.0	7878.0	8158.7
LC-RPL (COST + ITN)	69	-3901.2	7940.4	8221.1
LC-RPL (COST + MTB)	69	-3888.8	7915.6	8196.4
LC-RPL (COST + GFR + INFO)	89	-3603.3	7384.6	7746.7
LC-RPL (COST + GFR + INFO/OPN)	87	-3604.6	7383.2	7737.2
LC (COST + GFR + INFO/OPN)	50	-3785.3	7670.6	7874.0

803 Table 3: ANA rates retrieved from LC and LC-RPL models

Decision rule	**LC (%)**	**LC-RPL (%)**
Total attendance	50.6	72.2
ANA Cost	16.0	8.0
ANA Griffon vulture reintroduction	13.2	7.9
ANA Information centres + opening hours	13.9	7.0
Total ANA	6.3	4.9

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Table 4: LC and LC-RPL models results

	LC-RPL		LC		LC-RPL		LC		LC-RPL		LC		LC-RPL		LC		LC-RPL		LC	
	Class 1				Class 2				Class 3				Class 4				Class 5			
Class size (%)	**72.2**		**50.6**		**8**		**16**		**7.9**		**13.2**		**7**		**13.9**		**4.9**		**6.3**	
	Coeff.	MRS/pic	coeff	msr	coeff	msr	coeff	msr	Coeff	msr	coeff	msr	coeff	msr			coeff	msr		
Mean parameters β																				
ASC *Status quo*	-3.58	-10.52	-1.02	-3.92	-3.22	-23.04	-1.14	-8.14	-3.80	-17.27	-0.83	-41.5	-1.41	-20.14	-2.14	-71.33	-	-	-	-
	(9.18)		(16.18)		(1.99)		(2.24)		(4.74)		(6.32)		(6.61)		(5.25)		-	-	-	-
Bivouacs always open	0.24	0.71	-0.1	-0.38	0.08	0.57	0.12	0.85	0.04	0.18	-0.78	-39.22	0.04	0.57	-0.78	-25.99	-	-	-	-
	(1.11)		(1.09)		(1.07)		(1.22)		(0.33)		(3.11)		(0.41)		(1.11)		-	-	-	-
Bivouacs with food/firewood	1.09	3.21	0.62	2.38	0.28	2.01	0.15	1.07	0.92	4.18	0.84	42.01	0.76	10.86	-0.155	-5.17	-	-	-	-
	(6.06)		(7.15)		(0.82)		(1.08)		(2.54)		(4.63)		(5.31)		(0.52)		-	-	-	-
Congestion	-0.01	-0.03	-0.01	-0.04	-0.02	-0.14	-0.082	-0.59	-0.07	-0.31	-0.02	-1.03	-0.01	-0.14	-0.03	-1.02	-	-	-	-
	(2.79)		(9.50)		(3.72)		(1.97)		(4.18)		(2.46)		(6.17)		(0.88)		-	-	-	-
Entrance fee	-0.343	-1.01	-0.33	-1.27	-	-	-	-	-1.02	-4.63	-1.10	-55.1	-0.29	-4.14	-1.04	-34.67	-	-	-	-
	(4.52)		(18.48)		-	-	-	-	(5.23)		(12.02)		(9.11)		(0.94)		-	-	-	-
Gryphon vulture reintroduction	0.72	2.12	0.07	0.27	-0.15	-1.07	-0.12	-0.86	-	-	-	-	0.06	0.85	-0.35	-11.66	-	-	-	-
	(4.78)		(1.00)		(0.32)		(0.15)		-	-	-	-	(0.26)		(1.24)		-	-	-	-
Access to valleys	0.42	1.24	0.32	1.23	-0.68	-4.86	-0.14	-1.02	0.73	3.32	1.36	68.20	0.16	2.28	-0.13	-4.33	-	-	-	-
	(4.59)		(7.31)		(2.99)		(4.54)		(4.27)		(6.38)		(2.18)		(0.97)		-	-	-	-
Information centres	0.25	0.73	0.05	0.19	0.28	1.98	0.15	1.07	0.17	0.77	0.41	20.51	-	-	-	-	-	-	-	-
	(5.94)		(2.52)		(3.75)		(0.98)		(0.99)		(0.39)		-	-	-	-	-	-	-	-
Thematic itineraries	0.18	0.53	0.05	0.19	0.03	0.21	0.32	2.28	-0.89	-4.04	-0.01	-0.49	0.03	0.42	0.15	5.01	-	-	-	-
	(6.99)		(8.46)		(2.47)		(2.95)		(3.75)		(0.39)		(3.02)		(5.77)		-	-	-	-
MTB trails	0.18	0.53	0.06	0.23	0.18	1.28	0.49	3.51	1.25	5.68	0.86	43.21	0.18	2.57	0.25	8.33	-	-	-	-
	(2.39)		(2.09)		(2.58)		(15.42)		(3.91)		(7.80)		(3.88)		(3.17)		-	-	-	-
Opening hours info centres	-0.04	-0.12	-0.01	-0.04	0.03	0.21	0.09	0.64	0.20	0.91	0.01	0.52	-	-	-	-	-	-	-	-
	(2.79)		(2.88)		(0.77)		(0.12)		(3.21)		(1.60)		-	-	-	-	-	-	-	-
Picnic areas	0.34	1	0.26	1	0.14	1	0.14	1	0.22	1	0.02	1	0.07	1	0.03	1	-	-	-	-
	(3.44)		(3.2)		(2.75)		(1.99)		(3.45)		(2.55)		(5.52)		(3.44)		-	-	-	-
Standard deviations σ																				
ASC *Status quo*	0.32	3.57	-	-	0.65	31.62	-	-	0.07	0.11	-	-	0.22	2.98	-	-	-	-	-	-
	(1.88)		-	-	(2.45)		-	-	(3.52)		-	-	(0.93)		-	-	-	-	-	-
Bivouacs always open	0.24	2.61	-	-	0.21	10.05	-	-	0.10	0.15	-	-	0.15	2.00	-	-	-	-	-	-
	(1.01)		-	-	(0.71)		-	-	(0.32)		-	-	(0.49)		-	-	-	-	-	-
Bivouacs with food/firewood	0.22	2.42	-	-	0.15	7.55	-	-	0.13	0.19	-	-	0.41	5.61	-	-	-	-	-	-
	(1.97)		-	-	(2.61)		-	-	(5.23)		-	-	(3.33)		-	-	-	-	-	-
Congestion	0.04	0.05	-	-	0	0.13	-	-	0.02	0.02	-	-	0.09	1.27	-	-	-	-	-	-
	(2.10)		-	-	(0.06)		-	-	(2.46)		-	-	(0.85)		-	-	-	-	-	-

Note: Absolute values of *z* in brackets

Table 4: LC and LC-RPL models results *(continue)*

	LC-RPL		LC		LC-RPL		LC		LC-RPL		LC		LC-RPL		LC		LC-RPL		LC	
	Class 1				**Class 2**				**Class 3**				**Class 4**				**Class 5**			
Class size (%)	**72.2**		**50.6**		**8**		**16**		**7.9**		**13.2**		**7**		**13.9**		**4.9**		**6.3**	
	Coeff.	MRS/pic	coeff	msr	coeff	msr	coeff	msr	Coeff	msr	coeff	msr	coeff	msr			coeff	msr		
Mean parameters β																				
Entrance fee	0.92	10.28	-	-	-	-	-	-	-	-	-	-	0.07	0.91	-	-	-	-	-	-
	(11.82)		-	-	-	-	-	-	-		-	-	(3.92)		-	-	-	-	-	-
Gryphon vulture reintroduction	0.45	4.95	-	-	0.31	15.29	-	-	-	-	-	-	-0.10	1.41	-	-	-	-	-	-
	(2.84)		-	-	(3.42)		-	-	-		-	-	(1.51)		-	-	-	-	-	-
Access to valleys	0.04	0.5	-	-	0.26	-12.75	-	-	0.16	0.24	-	-	0.24	3.32	-	-	-	-	-	-
	(3.41)		-	-	(0.74)		-	-	(6.45)		-	-	(2.34)		-	-	-	-	-	-
Information centers	0.10	1.13	-	-	0.02	-0.78	-	-	0.03	0.04	-	-	0.03	0.43	-	-	-	-	-	-
	(3.88)		-	-	(4.01)		-	-	(0.15)		-	-	(2.47)		-	-	-	-	-	-
Thematic itineraries	0.08	0.89	-	-	0.12	0.17	-	-	0.56	0.83	-	-	-	-	-	-	-	-	-	-
	(4.56)		-	-	(0.34)		-	-	(5.54)		-	-	-		-	-	-	-	-	-
MTB trails	0.06	0.67	-	-	-0.27	-12.99	-	-	0.92	1.38	-	-	0.05	0.67	-	-	-	-	-	-
	(3.01)		-	-	(9.88)		-	-	(3.8)		-	-	(0.86)		-	-	-	-	-	-
Opening hours info centers	0.01	0.16	-	-	0.05	-2.65	-	-	0.3	0.46	-	-	-	-	-	-	-	-	-	-
	(8.08)		-	-	(2.06)		-	-	(3.51		-	-	-		-	-	-	-	-	-

Note: Absolute values of *z* in brackets

Table 5. Experimental design features (1 = attribute included in choice sets)

	Gryphon			Information centres			Opening hours		
	Hikers	MTB	Picnic	Hikers	MTB	Picnic	Hikers	MTB	Picnic
Wave 1	1	1	1	1	1	1	1	1	1
Wave 2	1	1	1	1	1	1	1	1	1
Wave 3	0	0	1	1	1	1	1	1	1
Wave 4	0	0	1	0	1	1	0	1	1

Table 6. Dirichlet regression estimates

	Class 1 (Total attendance)		Class 2 (ANA cost)		Class 3 (ANA Gryphon)		Class 4 (ANA Info + Hours)		Class 5 (Total ANA)	
Variable	**Coefficient**	**|t|**	**Coefficient**	**|t|**	**Coefficient**	**|t|**	**Coefficient**	**|t|**	**Coefficient**	**|t|**
Wave 1	-1.48	10.54	0.16	1.11	-0.20	2.58	-1.04	7.57	0.96	7.12
Wave 2	-1.14	8.02	0.28	2.08	-0.09	2.85	-0.23	1.72	0.83	6.78
Wave 3	-1.13	7.98	-0.03	0.24	0.50	1.01	-0.35	2.57	-0.04	0.90
Hikers	-0.13	1.08	-0.02	0.20	0.12	5.31	0.11	0.94	0.07	0.98
MTB	-0.07	0.62	-0.06	0.51	0.13	2.25	0.11	0.97	0.07	0.22

Figure 1: Percent change in choice probability for policy scenario 1

(one more picnic area in Val di Lamen)

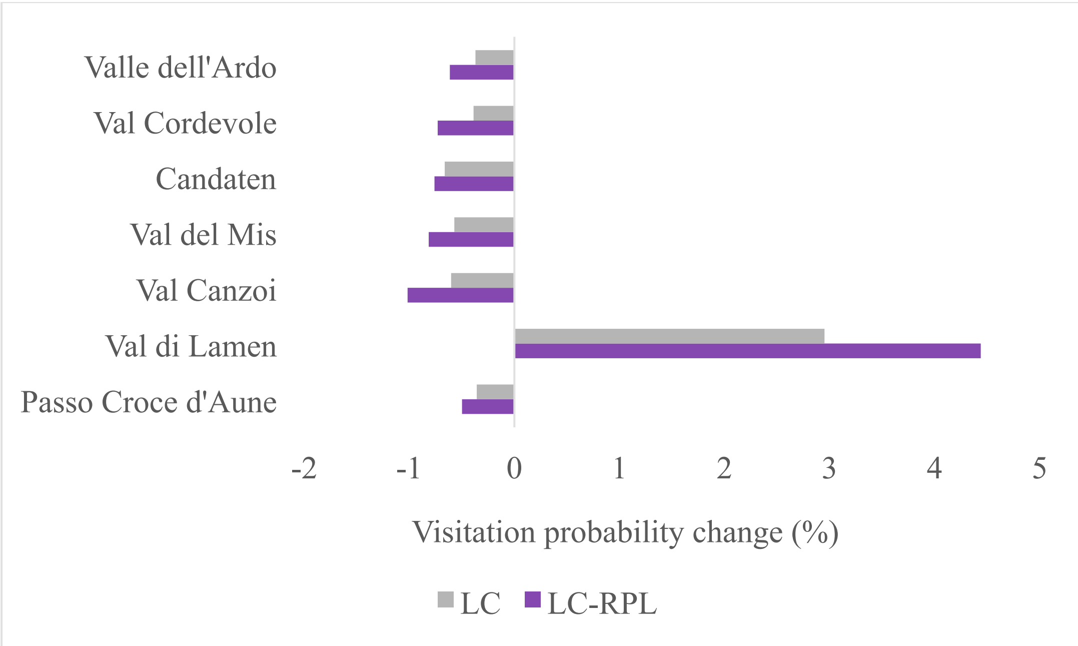

Figure 2: Percent change in choice probability for policy scenario 2

(one less picnic area in Val del Mis)