An alternative approach to identify protest attitudes in choices experiments

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Abstract

Protest responses have been a common topic in stated preference methods, and more specifically in Contingent Valuation (CV). However, there are few applications in Choice Experiments (CE) dealing with protest responses. In this work we present a novelty assessment of protest responses. Through attitudinal and follow-up questions and applying a Latent Class Model (LCM) we identify two different classes of respondents, that we denote protest and non-protest respondents. We analyze the heterogeneity between both groups and compared our results with a random parameter logit (RPL) model. The results show that if we do not take into account the protest beliefs in our estimations, we would be omitting some heterogeneity in the sample.

Keywords: Atlantic Islands National Park, attitudinal questions, choice experiments, latent class model, protest beliefs

4.1 Introduction

The treatment of protest bids in choices experiments (CE) has not been sufficiently investigated. In fact, just some previous studies have empirically studied protest in CE (Meyerhoff and Liebe, 2008; Meyerhoff and Liebe, 2009a). Meyerhoff and Liebe (2008) employ a follow up question with CE and CV to differentiate the protest beliefs and responses, and to assess whether the likelihood of protest responses differs across methodologies. They do not find clear differences between protests responses in both methodologies. Meyerhoff and Liebe (2009a) analyze the motives to select the status quo alternative. Furthermore, they assess the impact of the alternative specific constant for the status quo into the computation of compensating surplus. Due to the few existing references, the research in this field seems to be necessary, ever since the alternatives to deal with protest answers could have high influence on the results.

In other stated preference method, contingent valuation (CV), there is a huge amount of literature. Traditionally, the identification of protests has been done through a set of debriefing questions that are presented to those respondents who are unwilling to pay (Loomis et al., 1996, Strazzera et al., 2003), dropping them from the sample for welfare estimation purposes. However, numerous authors claim the need for a change in the identification and treatment (Jorgensen and Syme, 2000; Meyerhoff and Liebe, 2006), indicating that an unambiguously identification and treatment of protest and non-protest may be inappropriate. In fact, an identification of protest only among those that are not willingness to pay could be not adequate. The main justifying reason is that a protest attitude could be present in any type of respondent (Jorgensen et al., 1999).

In CV studies, some of the alternatives to deal with protest bids include the sample selection model, in which the protesters are identified among those that are not willing to pay (Strazzera et al., 2003); the identification of protest bids as real zero (Adams et al., 2007); or the inclusion of attitudinal questions to identify protest beliefs without eliminate them from the sample (Jorgensen and Syme, 2000). In the last years, some authors have noted the LCM as a good method to analyze protest responses in CV (Meyerhoff et al., 2009; Cunha-e-Sá et al., 2010) because it can be used to endogenously identify classes of individuals with similar characteristics, such as preferences or attitudes, according to their responses to survey questions. Following their reasoning, we believe that attitudinal information can provide signals about protest beliefs. Protest and non-protest responses may have different preferences, and consequently, their grouping into classes seems reasonable. Specifically, we assume that the answers to attitudinal questions are expressions of exogenous well-behaved preferences. To our knowledge this is the first application where, taking into account only attitudinal questions, it is analyzed the protest attitudes through a LCM in CE methodology.

Therefore the objectives of the current work are various. First, estimation of classes is performed using only attitudinal data containing answers to Likert-scale questions that let us differentiate between different types of protests beliefs such as those related with the lack of trust in the Government and its institutions, the unfairness to ask money or the inability to value the environment[3], among others. With this work we contribute to the protest literature in the stated preferences methods with an original component, the analysis in CE. Furthermore, we propose an alternative way to identify the influence of protest responses and their correct treatment in the stated preference framework. A second objective consists of the estimation of the individual preferences to manage a particular Galician ecosystem, the only National Park (NP) in the region, including the tourist and resident perceptions. The rest of this paper is structured as followed. In the *Literature Review* we look at the previous literature that has analyzed the heterogeneity in individual preferences through latent class models in different contexts. In the *Case Study Section*, we describe the survey employed and the area of study, the Atlantic Islands' National Park (AINP). In the *Empirical Specification* we present the models employed, the latent class and the random parameter logit for comparatives purposes. In the *Protest Response and Attitudinal Questions Section* we present the Likert scale used to investigate the heterogeneity and the protesters. Next, in the *Results Section* we present the main results obtained. Finally, in the *Conclusion Section*, some thoughts and concluding remarks are presented.

[3]This can be related with lexicographic preferences (Rekola, 2003), because participants are not able to do a trade-off between goods or attributes.

4.2 Literature Review

There are a variety of ways to include preference heterogeneity in choice models. The usual common way, it is through the inclusion of individual characteristics in the function, or through the differentiation among different groups based on observables characteristics (Hanley et al., 1998; FALTA ALGÚN). However, some studies have included attitudinal data to explain or as determinants of the individual's WTP (Willis et al., 1995; Alvarez-Farizo and Hanley, 2002). In fact, McFadden in 1986 suggested that attitudes and beliefs could be used to understand and estimated individual's preferences among products.

Latent Class (LC) modelling is one of several approaches for introducing heterogeneity in discrete choice analysis (Provencher and Moore, 2006). The underlying theory posits that individual behaviour depends on observable attributes and on latent heterogeneity that varies with factors that are unobserved by the analyst (Greene and Hensher, 2003).

LCMs are quite common in social sciences, and in the last years are becoming quite usual in environmental valuation studies (Morey et al., 2006; Boxall and Adamowicz, 2002; Provencher et al. 2002, Scarpa et al., 2003; Semeniuk et al., 2009). Some of these analyses have applied attitudinal questions to identify classes of respondents, but it is not a common practice. Provencher et al. (2002) use a LCM in a travel cost application to analyze the behavior of recreational anglers over the course of a season choice using only choice data. They assumed class probability to be conditional on individual's age and experience. Semeniuk et al. (2009) examine the heterogeneity of tourist preferences for wildlife management at a stingray-feeding attraction in the Cayman Islands. They uncover segments directly from the stated choice responses in underlying classes and test if these groupings differ in their management support. They asked attitudinal questions only with the purpose of explaining the latent groups in a decision-tree analysis. In the same line, Scarpa et al. (2003) use a LCM to identify the marked taste differences of the "creole" pig among the household sample in the state of Yucatan. Boxall and Adamowicz (2002) estimate a LCM with both attitudinal and choice data, conditioning preference class membership, which then drives the choice decision. In Morey et al. (2006), the attitude and choice data are driven by underlying preferences, which are identified by exogenous class membership variables.

RPL is a natural alternative to LCM. However, while RPL provides information about the extent of the heterogeneity, it provides no information regarding how preferences vary by individual characteristics (Morey et al., 2003). Boxall and Adamowicz (2002) have compared both models. They concluded that the RPL model identifies heterogeneity, but it is captured in a different way that in the case of LCM. In fact, they indicate that this last model enriches the traditional economic choice model by including psychological factors.

The latent class model used in this study tries to reflect the fact that protesters have different preferences than the rest of the population. In many previous studies, the identification of protesters is based in ad hoc criteria establish by each research. For that, the novelty in this study is that are the individuals themselves who with their answers will let the identification of a class of protesters aptitudes. To our knowledge only few previous unpublished studies have identified protesters through the LCM. In fact, this small amount of literature is focused on CV methodology (Meyerhoff et al., 2009; Cunha-e-Sá et al., 2010). In the work of Meyerhoff et al. (2009) the class membership is not dependent on attitudes, rather, attitudes are dependent on class; while Cunha-e-Sá et al. (2010) identify classes based on answers of individuals to an attitudinal question. We follow the second approach, that is, we identify different classes through attitudinal questions, which are a reflection of possible different preferences. Also, we estimated a RPL for comparative purposes in order to model and undertand the individual heterogeneity.

4.3 Case Study

The Spanish National Park's Network is an integrated system for protecting and managing the most valuable and representative areas of Spanish natural heritage. It is integrated by 14 NPs, with a total surface of 348000 hectares, which represents more than 0.6% of the total terrestrial surface of the country. The AINP is located in the southwest coast of Galicia (Spain). The total surface is 8480 hectares (7285.2 marines and 1194.8 terrestrial) and is formed by different archipelagos (Cíes, Ons, Sálvora and Cortegada). As we can observe in the map, the majority of the Park is a maritime surface, 86% of total (see Map 1).

In this paper we are going to estimate the preferences of the individuals with respect to different alternatives of management in the NP. Two are the main samples of analysis, tourists and residents. In Table 1, we present the socio-demographic characteristics. We include two reference populations, the Spanish sample for the tourist, and the Galician population for the residents. The percentage of male in the residents' sample is close to 48% and the females are 52%. These percentages are maintained in the tourist group, with 46% males and 54% females. In relation to the Spanish reference population, these percentages differ slightly, because in the Spanish's case the proportion of men and women are 49.5 and 50.5 % respectively. For the total sample, the average age is 42.5 years, a value that is below the Spanish and Galician samples (47.3 and 49.9 years, respectively). Furthermore, we should indicate that the age of tourist is 37.2 years, which is well below of the residents' age, 46.5. This difference could be explained by the fact that the majority of people that visit the NP are young.

Related with the educational levels, we note that the tourists surveyed have a high education level; with the 48.9% holding an university degree compared to 22.3% of residents. Even this rate is higher than the average value in the Spanish sample, which reaches 24.3%. Moreover, only the 6.1% of tourist have primary education or lower, as opposed to 36.4% of residents. On the other hand, the percentages of respondents with secondary school or professional education practically the same between each of samples.

The results show that the sample of tourist has the highest income, since the majority of tourists, 86.6%, have incomes above 19000 Euros per year, compared to the 48.72% of residents. This percentage for Spain is 59.3% and for Galicia 56.6%. Also, the tourists' sample differs from the residents' sample in the percentages of incomes fewer than 19000 Euros. This percentage reaches the 13.41% front of a 51.3% to residents.

4.3.1 Survey

The survey follows the same structure as previous surveys applied in other areas with slight novelties. The first part of the survey gathers views of respondents on various social problems, to continue with a question about whether they have previously visited the NP, which island, and when. The second part of the survey highlights the impact that the NP has in the area, asking which economic sector they consider that have been most influenced by the establishment of the Park, and in what direction. Then, we presented a series of statements about various measures that could be carried out in the NP, asking about the agreement or disagreement with each of them. In the third part of the questionnaire, we offered information about the NP. We showed the map presented above (Map 1), and asked questions about who are the most favored and disfavored by the declaration of NP, as well as, the perception of the degree deterioration due to different reasons.

In the fourth part of questionnaire, we presented to the respondents the principal actions that could be applied in the NP[4]. This description was supported with a card (Appendix). These actions have a hypothetic aspect, considering:

1. Increase of the NP's size (*size*), both marine and terrestrial. One of the alternatives is to include the Tambo Island, located in the middle of the Pontevedra's ria, in front of the village of Marin and with 28 hectares; and Estelas Islands, situated in front of Monteferro peninsula and with 19 hectares of surface. The other alternative is that the expansion, in addition to the islands mentioned above, includes also the Corrubedo Natural Park located in the A Coruña province and with an area of 996 hectares.
2. Decrease the number of visitors (*visitors*) in a 10% in the Cíes archipelago, and apply more control in the other Islands, because the control of the private transportation is quiet difficult.
3. Establishment of smoking areas (*smoke*), because of the increment of visitors in the summer raises the risk of fires by negligence.
4. Periodical actuations to avoid or reduce the alien species propagation and specifically the eucalypt.

Following this information, we present the different choice experiments (an example is the Figure 1) with two alternatives plus the "status quo[5]". Then, we ask respondents different questions about their decision, and a group of attitudinal questions that are

[4] Attributes were effects coded except the tax and size attributes, which were included as continuous variables.

[5] The Status Quo option indicates the current situation, which means do not anything.

described in the next section. Finally, the last part of the survey contains some ethics and socio-demographic questions.

4.4 Empirical Specification

The choice experiment method is consistent with utility maximization and demand theory (Bateman et al., 2002). Respondents are asked to choose between different bundles of (environmental) goods, which are described in terms of their attributes, or characteristics, and the levels that these take.

According to this framework, the individual *i*, from choosing an alternative *j*, have a utility function (U) of the form:

$$U_{ij}=V\left(Z_{ij},S_{ij}\right)+\varepsilon_{ij}=\beta X_{ij}+\varepsilon_{ij} \tag{1}$$

This indirect utility function can be described as a sum of two components: a deterministic part (V) and a stochastic part (ε). The first element is a function of the attributes of the different management scenario alternatives and the social characteristics (S) of the individuals. The second element represents unobservable influences on individual choices and it is independent of the deterministic part.

Thus, the probability that individual *i* chooses alternative *j* from a choice set to any alternative k, can be expressed as the probability that the utility associated with option *j* exceeds that associated with all other options (see equation 2). Assuming that the relationship between utility and attributes is linear in the parameters and variables function, and that the error terms are independently and identically distributed with a extreme-value (Weibull distribution) the probability of any particular alternative *j* being chosen as the most preferred can be expressed in terms of the logistic distribution.

$$P\left[\left(U_{ij} > U_{ik}\right) \forall j \neq k\right] = P\left[\left(\beta X_{ij} - \beta X_{ik}\right) > \left(\varepsilon_{ij} - \varepsilon_{ik}\right)\right] \tag{2}$$

Conditional logit is commonly used to estimate the choice modelling exercise. An assumption of the conditional logit is the distribution of the error terms, independently and identically distributed (IID). The violations of IID would imply violations in the independence of irrelevant alternatives (IIA) property. This property states that the ratio of choice probabilities between two alternatives in a choice set is unaffected by changes in that choice set (Alpizar et al., 2001). In order to test for IID/IIA violations, a Hausman-McFadden test was conducted, that basically involves constructing a likelihood ratio test around different versions of the model where choice alternatives are excluded. A χ^2 value of 135.47 was computed for a conditional logit model when ‘‘Option B’’ alternative was excluded from the choice set. This value exceeds the critical value (which from the Chi-squared table at 5% significance level with 5 degrees of freedom is 11.07). Therefore, the null hypothesis was rejected, indicating an IIA problem. This approach has been criticized by the limited ability to accommodate heterogeneous preferences (e.g McFadden and Train, 2000; Carlsson et al., 2003) because the IIA alternatives.

In this paper we are interested to account for heterogeneity in the preferences of the residents and tourists form the various management options of AINP attributes in function of protest beliefs. According with Swait (1994), heterogeneity can be addressed using latent class approaches or using heterogeneous model estimators like the random coefficient probit and logit models. For that, we have use for this paper the RPL model (Meijer and Rouwendal, 2000; Revelt and Train, 1998) and the LCM (Boxall and Adamowicz, 2002; Greene and Hensher, 2003) to try to asses the influence of attitudinal questions that may be behind protest beliefs. The former model allows heterogeneous preferences in the population, by allowing model parameters to vary randomly over individuals. However, as Boxall and Adamowicz (2002) point out, these models are not well-suited to explaining the sources of heterogeneity, which are related to the characteristics of individual consumers in many cases. Then, the probability of choice in the RPL model is given by:

$$\mathrm{P}_{ij}\left(j \text{ } is \text{ } chosen \mid \lambda_i \right) = \frac{\exp\left(\beta X_{ij} \right)}{\sum_k \beta X_{ik}} \tag{4}$$

where λ_i is an individual-specific random disturbance of unobserved heterogeneity. Following Lusk and Schroeder (2004), in general, the coefficient vector for individual *i* in the RPL is $\beta_i = \bar{\beta} + \sigma \lambda_i$, where $\bar{\beta}$ is the population mean, σ is the standard deviation of the marginal distribution of β , and λ_i is a random term assumed normally distributed mean zero and unit standard deviation. If $\sigma = 0$, then the RPL is equivalent to the conditional logit, and there is not heterogeneity.

The second model, the LCM, involves the characterization of different segments among the population. According to Boxall and Adamowicz (2002) the classification variables influencing segment membership are related to latent general attitudes and perceptions as well as socioeconomic characteristics of the individuals. In this approach, we assume the existence of S segments in a population and that individual *i* belongs to segment s. The utility function can now be expressed as

$$U_{ij|s} = \beta_s X_{ij} + \varepsilon_{ij|s} \tag{6}$$

where β_s is the segment specific vector of coefficients, X_{ij} is the vector of attributes associated with each alternative and $\varepsilon_{ij|s}$ is the random component of utility for each segment. Under the assumption of independently and identically distributed (iid) error terms that follow a Type 1 extreme value distribution, and since utility parameters are now segment specific the equation (3) becomes:

$$\Pr_{ij|s} = \frac{\exp\left(\beta_s X_{ij}\right)}{\sum_k \exp\left(\beta_s X_{ik}\right)} \tag{7}$$

where β_s is a segment-specific utility.

Membership to a specific segment is determined by an unobservable or latent likelihood function *M* that classifies respondents to one of the segments with probability P_{is} . For that, for a specific individual *i*, this function can be described by the following equation:

$$M_{is} = \lambda_s Z_i + \xi_{is} \tag{8}$$

where Z_i is a vector of socio-economic, attitudinal and other observed characteristics of the respondent *i* and segment s, λ_s is a vector of parameters and ξ_{is} is an error term. Assuming that this error term is also iid and follows a type 1 extreme value distribution, the probability that a respondent *i* belongs to segment *s* is given by

$$\Pr_{is} = \frac{\exp\left(\lambda_s Z_i\right)}{\sum_s \exp\left(\lambda_s Z_i\right)} \tag{9}$$

The joint probability that individual *i* belongs to segment *s* and chooses alternative *j* is given by

$$P_{ijs} = \left(P_{ij/s}\right) * \left(P_{is}\right) = \left[\frac{\exp(\beta_s X_{ij})}{\sum_k \exp(\beta_s X_{ik})}\right] * \left[\frac{\exp(\lambda_s Z_i)}{\sum_s \exp(\lambda_s Z_i)}\right] \tag{10}$$

The standard conditional logit is a special case of LCM because the joint probability in equation (10) reduces to conditional if $\lambda_s = 0$. In this case, the β_k s.are homogeneous and all individuals share a common utility function (Milton and Scrogin, 2006)

Different authors have pointed out the advantages that LCM has. First, the LCM does not require any specific assumption about the distributions of parameters across individuals (Green and Hensher, 2003). It is a semi-parametric approach, while in the RPL the preference parameters are assumed to have some assumed distribution, usually normal. Second, the LCM indicated the probability to belong to one class, taking into account that there is uncertainty about a respondent's class membership (Shen and Saijo, 2009)

4.5 Protest Responses and Attitudinal Questions

As we have mentioned, the attitudinal questions employed in our survey were presented with the objective to identify potential protest beliefs. Attitudinal questions to investigate protest beliefs have been previously used in some studies (Meyerhoof and Liebe, 2009; Jorgensen et al., 2001), although few are the attempts with LCM and none of them with LCM in CE. Table 4.2 presents the items used and their assignment to the protest or no protest category.

Once the choice sets where presented to the individuals, the attitudinal questions were asked. The answers were given on a five Likert scale. Also we present a question about the difficulty to answer of choice sets. The agreement with the variable *tootax*, "I pay enough taxes”, indicates that the individuals could be classified as protester Furthermore, those respondents that indicate that the government should use the collected funds and not seek other contributions, *collectedfunds*, tend to have a protest attitude. The lack of trust in Government is gathered through the variable *wastemoney*. The protesters are expected to be agreeing with the fact that if the Government does not waste the money, we might have a better management and control of the NP.

Those people who consider that it is unfair that they have to pay for the maintenance of the NP, *unfair*, are expected to be protesters. Moreover, protesters are expected to accept the idea that those who enjoy of Park should pay for the measures, *users*, when they are not visitors; and to refuse it in the case that they visit the NP. In our case, as we have both samples the final sign is not acquaintance. Finally, related with the attitudinal questions, those individuals that indicate that they cannot afford the payment nowadays, *nafford*, would be classified as non-protesters.

Furthermore, we include the variable *difficult*, which indicates the degree of difficulty encountered by the respondent to answer the choice sets. Although a priori the agreement with this variable could be expected that higher difficulty is related to protest responses, the opposite could also happen. Those individuals for whom the answers were more difficult would be those who spent more time to complete the survey, giving a more accurate response, indicating a non-protesters aptitude.

4.5.1 Econometric latent class model

The latent class model with attitudinal questions assumes that individuals with a similar attitude will show response patterns that are highly correlated (Meyerhoff et al., 2009). For that, a sample can be divided in a number of classes each one with a similar response pattern. From the attitudinal variables presented previously, the majority were included in the model through the Z_i vector in equation (10). The X_i vector consisted of the levels of five attributes associated with the management of the NP presented in the choice task. The log-likelihood (LL) function for a S-class model is:

$$\mathrm{LL}=\sum_{\mathrm{n}=1}^{\mathrm{N}} \sum_{\mathrm{m}} \sum_{j\in C_m} \delta_{nmj} \ln\left[\sum_{\mathrm{s}=1}^{\mathrm{S}} \left(\mathrm{P}_{\mathrm{ij/s}}\right)*\left(\mathrm{P}_{\mathrm{is}}\right)\right] \tag{11}$$

where N refers to the 871 individuals, m represents the 6968 choice sets and δ_{nmj} equals 1 if individual i choose j and 0 otherwise. The other symbols are described above.

4.5.2 Criteria for number of classes

The number of classes, S, is unknown a priori. Previous research has used a number of indicators for choosing the optimal number of groups, recognizing hat these indicators are only suggestive (Wedel and Kamakura, 2000), and as Swait (2007) points out, always it is necessary use the common sense and simplicity. In this analysis the log likelihood, the consistent Akaike information criteria (CAIC), the Bayesian information criteria (BIC) and the Bozdogan Akaike information criteria (AIC3) were used. Comparing the criteria among the different models estimates with a varying number of classes will help us to decide the final number of groups.

The CAIC can be calculates as

$$\text{CAIC} = -2\text{LL} + \left[1 + \text{Ln}\left(\text{N}\right)\right]\text{P} \tag{12}$$

The formulae of BIC and AIC are respectively,

$$\text{BIC} = -2\text{LL} + \text{Ln(N)P} \tag{13}$$

and

$$\text{AIC3} = -2\text{LL} + 3\text{P} \tag{14}$$

In Table 4.3, the calculations of these criteria are presented as well as for the RPL. As we can see all the statistics indicate that the two class model is the optimal number of classes.

4.6. Results

The estimation results for the LCM and the RPL are presented in Tables 4.4 and 4.5 respectively. Note that the parameters of attitudinal variables for the second class are equal to 0 due to their normalization during the estimation. Consequently, the probability of belonging to this first class must be described relative to the second class which was called “protesters”. The other class, latent class 1, is designed as the “non-protesters”. The reason is that for this class, the probability that an individual agrees with the fact that he/she pays too many taxes (*tootax*) decreases. Also, the variable *collectedfunds* is negative and significant, indicating that the respondents who agree with the fact that the Government should use the funds that they have and not seek more are less likely to be in this class. The same sign and significance have the variables *unfair* and *users*. That means that individuals that consider that is unfair to ask them for money to maintenance the NP are less likely to belong to class 1. The *users* variable shows that the individuals who consider that only the users should pay are less likely to belong to the first class. Confirming the identification of the different classes, we can observe the sign and significance of the variable *nafford*. The positive sign indicates that those individuals who agree with the fact that they cannot afford the payment nowadays have a higher likelihood to be found in the non-protester class. Lastly, the variable *difficult* has a positive and significant sign. This means that the respondents who pointed out higher degrees of difficulty to answer the choice sets, have higher likelihood to be in the non-protester class. As we have mentioned, this can relate to the fact that non-protesters are those who spend more time thinking about their answers, providing a more realistic response.

If we focus in the utility function parameters$\left(\beta_s\right)$, we can note that *tax* is negative and significance in both classes, being consistent with the economic theory. Only, the sign of the attribute *smoke* changes across classes, while in the non-protesters class is positive, for the protesters it is negative. This means that protesters would not agree with creating smoking areas in the AINP. Also, we have included some socio-demographic characteristics of individuals, the age (*age*) and the fact that previously they visited the NP (*pvisit*). We have two estimates of each of these variables related with the alternative A or B. Their interpretation should be done with respect to the status quo alternative.

In the case of non-protesters, only the age for the alternative B is significant, this means that the utility of the individuals in this class decreases when their age increases. However, in protesters class, all the coefficients are negative and significant. The individuals with more age and those that have visited previously the NP have less utility than those with less age and that never visited the Park. This can be a signal of the fact that in the protester class the characteristics of the individuals are more homogeneous, while that the non-protesters class the socio-demographic characteristics are not very decisive. The average class probabilities indicate that 63.5% of sample are member of the non-protester class and a 35.1% of the protester class.

The RPL are presented in Table 4.6. The only fixed (equal among individuals) variable is *tax*, while the others variables were assumed to be normally distributed across the individuals in the sample. The coefficient of *tax* is negative and significant according to the economic theory. The rest of the coefficients are significant and positive, that is, we obtain the same results that for the class protesters. Related to the socio-economic characteristics of the respondents, we observe that, in general, increments in age decrease the utility of individuals. Also, the fact that the individuals visited the NP previously decreases their utility, although this is only significant for the alternative B.

The presented models suggest that respondents have positive preferences for the different attributes[6]. However while in the non-protester class of LCM the utility of respondent increases when a smoking area is created, in the protester class occurs the opposite, the utility decreases. It is obvious that the results of the non- protester class are more similar to the results of the RPL. Therefore, including only the estimations of this model without any analysis of protest attitudes could lead to a loss of information about the heterogeneity of preferences, specifically some preferences of the protesters.

4.6.1 Welfare estimations

To see how the individuals evaluate the different management alternatives in the AINP, and analyze how the protest attitudes influence through a monetary value, the

[6] Following Camarena and Sanjuán (2005) we have estimated the amount of individuals that prefer each level of attributes. According with the expression

$$\text{Prob}[\beta_{attribute} > 0] = \text{Prob}\left[z > \frac{0-\beta_{attribute}}{S_{attribute}}\right] = 1-\text{Prob}\left[z \le \left(-\frac{0-\beta_{attribute}}{S_{attribute}}\right)\right]$$

The results indicate that the 66.4% of the respondents prefer the creation of smoking areas, whereas the 33.6% do not prefer it. Eighty percent and 66.9% prefer the control of visits and the increment of area of NP respectively. Finally, 68% prefer the control of alien species, specifically actuations with the eucalyptus.

willingness to pay values (WTP) were calculated. Respondents' WTP is given by the following equation:

$$WTP_{attribute/s} = \frac{\beta_{attribute/s}}{\beta_{tax/s}} \tag{14}$$

where $\beta_{attribute/s}$ are the estimated parameters associated with the attributes *size, visits*, *smoke* and *eucalypt* in each class, protester and non-protester, and $\beta_{tax/s}$ for the *tax* attribute in each class. According to Shen and Saijo (2009) because these two coefficients vary across classes, the estimated WTP values could identify heterogeneity among individuals. For the RPL, the equation is the same; the only difference is that there is no classes, that means that we have one estimation for each attribute. Furthermore, the class probability weighted WTP was estimated for the LCM. The equation is:

$$WTP_{weithted} = \sum_{s=1}^{2} WTP_{attribute/s} * Prob_s \tag{15}$$

where $Prob_s$ is the probabilities of respondents in class s.

The results are presented in Table 4.6. We observe that the values vary across classes and models. In general the WTP estimations for the non-protester class and the weighted WTP are larger than those corresponding values for the RPL. If we focus on the welfare estimations of the different identified classes, we can see that the WTP for non-protest and protest are different, being higher in the first class for all the attributes. That confirms the expected results about that protesters usually provide lower WTP values. Related to the RPL results, only the attribute *size* has a higher value comparing with the weighted WTP and the non-protesters' WTP. However, in the case of protest class the estimates are always lower. Therefore, we can conclude, that although the RPL model includes the protest effect in their estimations, we cannot observe explicitly which effect is. This does not happen if we have different classes, because we can distinguish the influence of these different attitudes and preferences in the results. Moreover, the weighted WTP is a good measure because takes into account both classes of respondents and their preferences. With the weighted WTP we take into account the protest beliefs not through an arbitrary identification. Classical approaches have dropped the sample of protests from estimations usually by ad hoc criterion, with some consequences as elimination of part of the sample and even the loss of part of the information. This methodology allows us to maintain the entire sample, but taking into account the fact that part of it has a different attitude towards the good, valued to the mechanism to be evaluated or even towards the Government .

4.7. Conclusions

In this paper we have used attitudinal questions to identify protests and non-protests among the residents and tourists in the AINP. We have presented to the individuals different alternatives of management. The attributes included the possibility of reducing the number of visits, the control of alien species, the creations of smoking areas and the increment of the size of the NP. We have estimated a LCM and a RPL model. Both models offer alternatives ways of capturing unobserved heterogeneity (Green and Hensher, 2003). However, in our empirical application and with our objective to explain part of the heterogeneity through the protest behaviour of respondents, the LCM appears to be more appropriate. Using attitudinal questions about taxes (*tootax*), the use of existing funds (*collectedfunds*) or the impossibility to afford nowadays a payment (*nafford*), among others, allowed us to identify heterogeneity preferences between the two different classes, called protesters and other non-protesters.

The LCM, which provides a much richer interpretation of behavior of individuals to the management actions, indicates that the protesters are related in general with lower willingness to pay for the measures. Also, the protesters class expressed negative preferences for the creation of smoking areas in the AINP. In the RPL the results show the existence of heterogeneity in the sample. Moreover, the welfare estimations are lower than those from the non-protesters class, and higher than the protesters.

In the traditional literature, the majority of the empirical applications only represent the preferences of individuals classified as being non-protest responses. Comparing with the class identified as non-protesters in the LCM, the weighted WTP allows us to present a unique measure that takes into account the preferences of all individuals, protesters and non-protesters. Also, other advantage is linked to the fact that this identification was made without the application of arbitary rules,, because the answers of respondents to the attitudinal questions are the elements that determinate the weight of protesters ´preferences.

As we have mentioned few are the empirical analyses of protest responses in CE results. The majority of the analyses and studies were applied with the CV method. Following this line, we applied a LCM to the protest problem in CE. To our knowledge this is the first application in CE, while overall little has been done previously in other stated preferences methods. With the obtained results, we consider that this approach can be an alternative to the traditional way to identify and treat protesters.

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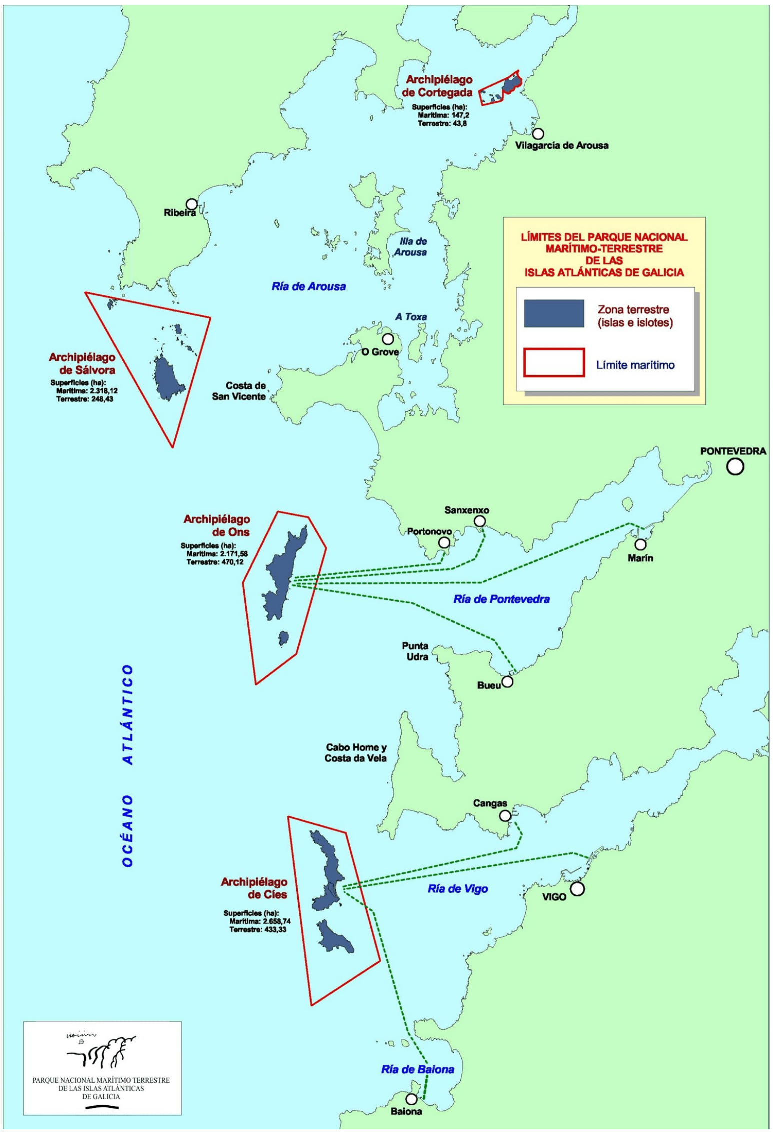
Map 4.1. Atlantic Islands National Park



Source: OAPN (2009)

Figure 4.1. Example of choice experiment presented in the survey

	Option A	**Option B**	**Status Quo**
Increase of the Atlantic Island National Park's <u>size</u>	 1024 ha	 1024 ha	0 ha
Decrease the number of <u>visitors</u> in Cíes in a 10% and increase the control in others islands.	X NO	V YES	X NO
Establishment of <u>smoking areas</u> and avoid the fire risk.	V YESI	X NO	X NO
Periodical actuations to <u>control the Eucalyptus</u>, alien species that causes the loss of biodiversity	X NO	V YES	X NO
Punctual <u>tax</u> (€)	**15€**	**30€**	**0€**
Choose (please, choose the preferred)			
Rank from high to low your preference			

Table 4.1. Socio-economic characteristics of samples

Socio-economic Characteristics	Total Sample	Reference Sample (Spain)	Reference Sample (Galicia)	Tourists	Residents
Age average	42.5	47.3	49.9	37.2	46.5
Studies					
Primary school or lower	21.1	31.7	42.4	6.1	36.4
Secondary School and Trainer Formation	42.7	43.9	35.9	44.6	40.8
Higher Education	35.7	24.3	21.6	48.9	22.3
Gender					
Male	46.8	49.5	48.3	46.1	47.6
Female	53.2	50.5	51.7	53.9	52.4
Household Annual Income					
≤9000 Euros	3.7	12.6	14.6	0.9	6.5
9000 - 14000 Euros	13.3	13.5	14.1	4.6	22.3
14000 - 19000 Euros	15.5	14.6	14.7	8.0	22.5
19000 - 25000 Euros	28.6	15.6	16	24.6	32.7
25000 - 35000 Euros	20.9	19.7	21	28.0	13.7
>35.000 Euros	18.4	24	19.6	34.1	2.32
Number of respondents	871			440	431

Table 4.2. Attitudinal questions and Difficulty of Choices Sets to identify protesters and non-protesters

Variable	Affirmations	Protest Attitude
	Attitudinal Questions[7]	
Tootax	I pay enough taxes	Agree
Collectedfunds	The government should use the collected funds and not seek other contributions	Agree
Wastemoney	If the Government did not waste the money, we could have a better management and control of the National Park.	Agree
Unfair	It is unfair asking money to maintain the National Park	Agree
Users	Those who enjoy of Park should pay for the measures	Agree or disagree
Objectives	I do not believe that the collected money were used for these objectives	Agree
NAfford	I cannot afford the payment nowadays	Disagree
	Respondents' Understanding[8]	
Difficult	Indicate the degree of difficult to answer the previous choices experiments about the different management alternatives in the National Park Atlantic Islands.	Agree or disagree

[7] Completely Agree, Agree, Neither Disagree nor Agree, Disagree, Completely Disagree.
[8] A scale from 1 to 10, with 1= nothing difficult and 10=extremely difficult.

Table 4.3 Information criterions for different number of classes

Number of classes	Number of parameters (P)	Log Likelihood (LL)	CAIC	BIC	AIC3
2	26	-5527.304	11310	11284	11133
3	43	-6083.923	12591	12548	12297
4	60	-6101.727	12794	12734	12383
RPL model	13	-6216.996	12562	12549	12473

Table 4.4. Latent Class Model

Attribute	Latent Class 1 Non protesters: Coefficient (Std. Err.)	Latent Class 1 Non protesters: Z	Latent Class 2 Protesters: Coefficient (Std. Err.)	Latent Class 2 Protesters: Z
Size	1.487 (0.149)	9.987***	0.120 (0.039)	3.096***
Visits	0.861 (0.145)	5.958***	0.137 (0.033)	4.157***
Smoke	0.623 (0.083)	7.523***	-0.123 (0.033)	-3.696***
Eucalypt	0.685 (0.030)	23.035***	0.369 (0.033)	11.056***
Tax	-0.070 (0.038)	-1.872*	-0.111 (0.024)	-4.698***
Pvisit (A)	0.172 (0.219)	0.786	-0.498 (0.095)	-5.221***
Age (A)	0.003 (0.005)	0.552	-0.038 (0.002)	-16.605***
Pvisit (B)	-0.097 (0.232)	-0.420	-0.467 (0.094)	-4.955***
Age (B)	-0.010 (0.005)	-1.973**	-0.039 (0.002)	-16.462***
	Theta(1) in class probability model		***Theta(2) in class probability model***	
Constant	6.842 (0.496)	13.792***	0	(Fixed Parameter)
Tootax	-0.606 (0.086)	-7.007***	0	(Fixed Parameter)
Collectedfunds	-0.463 (0.079)	-5.864***	0	(Fixed Parameter)
Unfair	-1.010 (0.054)	-18.764***	0	(Fixed Parameter)
Wastemoney	-0.120 (0.075)	-1.591	0	(Fixed Parameter)
Users	-0.002 (0.001)	-3.234***	0	(Fixed Parameter)
NAfford	0.237 (0.047)	4.995***	0	(Fixed Parameter)
Difficult	0.231 (0.021)	10.860***	0	(Fixed Parameter)
Average class probabilities	0.635		0.351	
Log-likelihood	-5527.304			
AIC	1.6179			
BIC	1.6437			

McFadden Pseudo R-squared	0.27
Number of observations	6865

***, **, * = coefficients significantly different from zero at 0.1%; 1%; and 10% significance level.

Variable Definition:

Pvisit	=1 if previously had visited the National Park; =0 otherwise
Age	Age of respondents

Table 4.5. Random Parameter Logit Model

Attribute	Coefficient (Std. Err.)	Z
Random parameters in utility functions		
Size	7.860 (2.202)	3.570***
Visits	1.651 (0.304)	5.436***
Smoke	0.938 (0.254)	3.687***
Eucalypt	3.720 (1.157)	3.216***
Non random parameters in utility functions		
Tax	-0.554 (0.195)	-2.842***
Pvisit (A)	-0.762 (0.592)	-1.287
Age (A)	-0.134 (0.040)	-3.354***
Pvisit (B)	-0.895 (0.344)	-2.606***
Age (B)	-0.088 (0.014)	-6.235***
Derived standard deviations of parameter distributions		
Size	17.994 (5.489)	3.278***
Visits	1.957 (0.509)	3.848***
Smoke	2.211 (0.583)	3.794***
Eucalypt	7.954 (3.337)	2.383**
Log-likelihood	-6216.996	
AIC	1.815	
BIC	1.82794	
Pseudo R²	0.18	
Chi-squared	2649.955	
p-value	0.000	
Nº observations	6865	

***, **, * = coefficients significantly different from zero at 0.1%; 1%; and 10% significance level.

Variable Definition:

Pvisit	=1 if previously had visited the National Park; =0 otherwise
Age	Age of respondents

Table 4.6. Welfare Estimations of LCM and RPL

	LCM		RPL
	WTP (95% C.I.)	**WTP weighted (95% C.I.)**	**WTP (95% C.I.)**
	Non-protesters		
Size	21.16 (2.09, 40.23)	13.82 (1.44, 26.19)	14.20 (7.26,21.13)
Visits	24.51 (14.89, 34.13)	16.42 (10.06, 22.79)	5.97 (4.15,7.78)
Smoke	17.73 (10.17, 25.29)	10.48 (5.41, 15.54)	3.39 (2.30,4.47)
Eucalypt	19.50 (9.41, 29.58)	14.71 (7.80, 21.62)	13.44 (8.99,17.88)
	Protesters		
Size	1.08 (0.31, 1.84)		
Visits	2.45 (1.73, 3.19)		
Smoke	-2.22 (-2.97, -1.47)		
Eucalypt	6.63 (5.19, 8.07)		

* Confidence intervals have been calculated employing the delta method