Incorporating environmental attitudes in discrete choice models: an exploration of the utility of the awareness of consequences scale

David Hoyos

Department of Applied Economics III (Econometrics and Statistics), University of the Basque Country (UPV/EHU)

Avda. Lehendakari Aguirre, 83. E48015 Bilbao, Spain

E-mail: david.hoyos@ehu.es

Tel: +34.94.601.7019

Fax: +34.94.601.3754

Petr Mariel

Department of Applied Economics III (Econometrics and Statistics), University of the Basque Country (UPV/EHU)

Avda. Lehendakari Aguirre, 83. E48015 Bilbao, Spain

E-mail: petr.mariel@ehu.es

Tel: +34.94.601.3848

Fax: +34.94.601.3754

Stephane Hess

Institute for Transport Studies

University of Leeds, UK

E-mail: s.hess@its.leeds.ac.es

Abstract

Environmental economists are increasingly interested in better understanding how people cognitively organise their beliefs and attitudes towards environmental change in order to identify key motives and barriers that stimulate or prevent action. In this paper, we explore the utility of a commonly used psychometric scale, the awareness of consequences (AC) scale, in order to better understand stated choices. The main contribution of the paper is that it provides a novel approach to incorporate attitudinal information into discrete choice models for environmental valuation: firstly, environmental attitudes are incorporated using a reinterpretation of the classical AC scale recently proposed by Ryan and Spash (2012); and, secondly, attitudinal data is incorporated as latent variables under a hybrid choice modelling framework. This novel approach is applied to data from a survey conducted in the Basque Country (Spain) in 2008 aimed at valuing land-use policies in a Natura 2000 Network site. The results are relevant to policy-making because choice models that are able to accommodate underlying environmental attitudes may help in designing more effective environmental policies.

Keywords: discrete choice; valuation; Hybrid Latent Class (HLCM) model; choice modelling; latent attitudes; Natura 2000

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1. Introduction

Environmental issues such as climate change, the depletion of natural resources and biodiversity loss increasingly threaten the welfare of human civilisation. Confronting these threats requires, among other things, behavioural changes in citizens, governments and companies. Environmental psychology has been devoted to investigating human behaviour and ways to influence it in order to avoid environmental degradation. Theoretical models aiming at a better understanding of how people cognitively organise their beliefs and feelings towards environmental change may help identify the key motives and barriers that stimulate or prevent action. Ultimately, understanding these motives and barriers to human action or inaction may help to design more effective environmental policies.

Economists have been historically more interested in analysing the results of rational choice rather than the process of choice (Simon, 1978), however, it is clear that understanding human behaviour requires a deep understanding of the motives behind, as well as the motives for, action. As a consequence, the psychological process underlying an observed willingness to pay (WTP) response has been receiving increasing attention. WTP to protect natural resources is the product of a highly complex psychological process, with many different factors influencing observed responses at many different levels. Respondent starting points on valuation questionnaires differ not only in terms of their socioeconomic characteristics or their level of prior information but of their environmental attitudes and their perception of the environmental issue under valuation (Dietz et al., 2005). So, WTP responses can be interpreted as behavioural intention (Bateman et al., 2005). The question is whether environmental attitudes are good predictors of environmental intentions such as WTP.

The most popular behavioural theory in environmental psychology is the value-belief-norm (VBN) theory (Stern et al., 1993; 1995). The VBN theory proposes that egoistic, altruistic and biospheric value orientations influence the way in which individuals formulate and structure environmental beliefs (Stern, 2000). The measurement of the model’s proposed environmental beliefs has mainly been taken using psychometric scales such as the awareness of consequences (AC) scale, constructed over three subscales: egoistic, altruistic and biospheric value orientations. Although studies using different versions of the AC scale have found that people do cognitively construct positions that are consistent with the VBN theory's subscales, it is not uncommon to find poor dimensionality and reliability, as well as theoretically inconsistent subscale correlations (Snelgar, 2006; Hansla et al., 2008; Ryan and Spash, 2012). Given the empirical limitations in measuring AC beliefs, Ryan and Spash (2012) have recently reinterpreted the scale as a measure of beliefs supporting environmental action and inaction (BSEAI scale). Beliefs supporting environmental action can also be divided into beliefs in the positive consequences of environmental protection and in the seriousness of environmental damages (see Table 1).

[TABLE 1]

Disentangling the motives behind WTP values is clearly not an easy task, although attitudes and ethical beliefs have been frequently found to motivate responses to WTP questions (Pouta, 2004; Spash, 2000; Stern et al., 1995; Spash and Hanley, 1995). Attempts have also been made to use value orientation based belief scales to interpret the motivations behind stated preference valuation studies (Ojea and Loureiro, 2007; Spash, 2006). Given the empirical limitations revealed in the classical AC attitudinal scale, in this paper we will analyse attitudinal data using the BSEAI scale.

Discrete choice experiments are being increasingly used in environmental valuation studies (see e.g. Can and Alp, 1012 and Justes et al., 2014). Recent developments in discrete choice modelling have also attempted to incorporate the ethical and attitudinal characteristics of respondents. Although the development of mixed logit models has allowed researchers to incorporate unobserved heterogeneity, it is clearly preferable from an interpretational point of view to explain as much as possible of this heterogeneity through interaction with characteristics of the respondents, such as age, gender or attitudinal data. Attitudinal data is typically collected by asking respondents to indicate their degree of agreement with a number of attitudinal statements (Eagly and Chaiken 1993; 2005). Attitudinal variables have mainly been incorporated in stated choice models using additional explanatory variables of indirect utility function (e.g. Milon and Scrogin, 2006). This approach has two major drawbacks, however: answers to attitudinal questions are not direct measures of attitudes but functions of underlying latent attitudes; and answers to attitudinal questions may be correlated with unobserved factors, thus leading to endogeneity bias (Hess and Beharry-Borg, 2012). In order to deal with these issues, hybrid choice models have been proposed (Ben-Akiva et al., 1999; Ashok et al., 2002; Ben-Akiva et al., 2002; Bolduc et al., 2005). Starting from the premise that attitudes themselves are not observed, hybrid choice models treat indicators as dependent variables instead of explanatory variables, and jointly model responses to the stated choice component and responses to the attitudinal question. The link between the two components is made through latent variables relating to underlying attitudes.

This paper aims to explore whether incorporating attitudinal information using validated psychometric scales provides additional insights into the analysis of discrete choices. The main contribution of the paper is that it provides a novel approach to incorporate attitudinal information into discrete choice models for environmental valuation: firstly, environmental attitudes are incorporated using a reinterpretation of the classical AC scale recently proposed by Ryan and Spash (2012); and, secondly, attitudinal data is incorporated as latent variables under a hybrid choice modelling framework. This novel approach is applied to a DCE conducted in the Basque Country (Spain) in 2008 aimed at valuing land-use policies in a Natura 2000 Network[1] site (Hoyos et al., 2012). The results are relevant to policy-making

[1] The European Natura 2000 network aims to ensure the long-term protection of Europe's most valuable and threatened species and habitats. It currently includes 5,315 Special Protection Area (SPA) sites

because choice models that are able to accommodate underlying environmental attitudes may help in designing more effective environmental policies.

The rest of the paper is structured as follows: Section 2 describes the methodology used; Section 3 presents the empirical application; Section 4 provides with the main results; and finally, Section 5 discusses the results and presents the main conclusions of the research.

2. Methodology

The gap between discrete choice models and behavioural theory has encouraged different developments in attempting to enrich the behavioural realism of discrete choice models, by explicitly modelling one or more components of the respondents' decision-making process (e.g. accounting for attitudes and perceptions) or employing more flexible error structures in the specification of the utility function (see for example Ben-Akiva et al., 2002; or Train, 2003). The most general framework proposed is the integrated choice and latent variable methodology (Ben-Akiva et al., 1999; Ashok et al., 2002; Ben-Akiva et al., 2002; Bolduc et al., 2005). This hybrid modelling approach integrates latent variable and latent class models with discrete choice methods to model the influence of latent variables and classes on the choice process. Latent variable models capture the formation and measurement of latent psychological factors, such as attitudes and perceptions, which explain unobserved individual heterogeneity. Latent class models also capture unobserved heterogeneity by modelling latent segments of the population that could, for example, differ in their choice sets or decision protocols. Hybrid choice models have been applied primarily in the transport field (see e.g. Glerum et al., 2012 or Daly et al., 2012) but have also recently been moved into environmental valuation (Hess and Beharry-Borg, 2012).

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encompassing 593,486 square kilometres, and 22,529 sites of community importance (SCI), (719,015 km^2), covering around 18% of the EU land area (European Commission, 2011).

Instead of directly incorporating latent variables in the choice model, Hess et al. (2012) opt for a latent class framework in which respondents are allocated to classes according to underlying attitudes that also influence their responses to environmental attitudinal questions (a hybrid latent class model (HLCM)). Following this approach, attitudes are considered to be latent variables in this paper, and are used in the class allocation function of a classical LC model. This hybrid modelling framework describes how attitudes affect choices through class allocation probabilities, and at the same time uses observed choices as feedback for estimation of the latent attitudinal variables. The aim of this approach is to adequately capture individual taste heterogeneity through attitudinal indicators. Some of the heterogeneity may be related to the socio-demographic characteristics of respondents but non-observed attitudes may in fact be the main cause of heterogeneity (Small et al. 2005; 2006). In line with Hess and Beharry-Borg (2012) and Daly et al. (2012), we take into account both the repeated choice nature of the data and the ordinal nature of the attitudinal indicators.

Breffle et al. (2011), in an environmental application, also assume that using attitudinal data in addition to choice data provides an opportunity to enhance the understanding of preference heterogeneity but their approach is fundamentally different: the link between the choice and preference-statement part of the model is obtained solely through the log-likelihood function and any socio-demographics used in the class allocation drive both the choices and the follow-up questions in the same way. Our approach breaks the absolute relationship between a given class in terms of the taste coefficients and answers to the follow-up questions, allows for measurement error in the follow-up questions, and allows for different socio-demographic interactions in underlying attitudes and for class allocation in the choice model.

The HLCM requires the specification of two types of structural equations, one for the choice model and one for the latent variable model. The structural equation for the choice model is based on the random utility theory (cf. McFadden, 1974), which is used to link the deterministic model with a statistical model of human behaviour. Under this framework, the utility of alternative *i* for respondent *n* in choice situation *t* is given by:

$$U_{int} = V_{int} + \varepsilon_{int}, \tag{1}$$

where V_{int} is a term linked to some explanatory variables and ε_{int} is a random variable following an extreme value distribution with location parameter 0 and scale parameter 1. In a classical random utility model, the term V_{int} depends on observable explanatory variables, which are usually attributes (x_{int}) and vectors of attribute parameters β. In addition, alternative specific constants (ASC) are included for two of the three alternatives.

Latent class models are based on the assumption that individuals can be sorted into a set of C classes, each of which is characterised by unique class-specific utility parameters β_C. Given membership of class c_s, the probability of respondent n's sequence of choices is given by

$$P_n = \Pr(y_n^t | c_s, x_n) = \prod_{t=1}^{T_n} \frac{\exp(ASC_i + \beta'_{c_s} x_{int})}{\sum_{j=1}^{J} \exp(ASC_i + \beta'_{c_s} x_{jnt})}, \tag{2}$$

where y_n^t is the sequence of choices over the T_n choice occasions for respondent n and ASC_i is an alternative specific constant for alternative *i* normalised to zero for one of the J alternatives. Equation (2) is a product of MNL probabilities. The LC framework recognises that actual membership of a class is not observed, it is latent. If the probability of membership of a latent class c_s of respondent n is defined as π_{n,c_s}, the unconditional probability of a sequence of choices can be derived by taking the expectation over all C classes, that is

$$P_n = \Pr(y_n^t | x_n) = \sum_{s=1}^{C} \pi_{n,c_s} \prod_{t=1}^{T_n} \frac{\exp(ASC_i + \beta'_{c_s} x_{int})}{\sum_{j=1}^{J} \exp(ASC_i + \beta'_{c_s} x_{jnt})}. \tag{3}$$

The class allocation probabilities π_{n,c_s} are usually modelled using a logit structure, where the *utility* of a class is a function of the socio-demographics of the respondent (SD_n) and parameters (λ_s), in addition to an constant, μ_{0s}, for class *s*.

The second structural equation refers to the latent variable model, so that the structural equation for the *q*-th latent variable of total *Q* is given by

$$LV_{qn} = h(Z_n, \gamma_q) + \omega_{qn}, \tag{4}$$

where $h(Z_n, \gamma_q)$ represents the determinist part of LV_{qn} and the specification $h(\cdot)$ which is in our case linear with Z_n being a vector of the socio-demographic variables of respondent n, and γ_q being a vector of parameters. Additionally, ω_{qn} is a random disturbance, which is assumed to be normally distributed with a zero mean and standard deviation $\sigma_{q\omega}$.

Measurement equations use the values of the attitudinal indicators as dependent variables, and explain their values with the help of the latent variables. The ℓ^{th} indicator (of total L_q indicators) for respondent n is therefore defined as

$$I_{q\ell n} = m(LV_{qn}, \zeta_q) + v_{qn}, \tag{5}$$

where the indicator $\boldsymbol{I_{q\ell n}}$ is a function of latent variable $\boldsymbol{LV_{qn}}$ and a vector of parameters $\boldsymbol{\zeta_q}$. The specification of $\boldsymbol{v_{qn}}$ determines the behaviour of the measurement model and depends on the nature of the indicator.

Responses to attitudinal statements are collected using a Likert type response scale, so that the measurement equations are given by threshold functions. For a discrete indicator with $\boldsymbol{K}$ levels $\boldsymbol{i_1}, \boldsymbol{i_2}, \dots, \boldsymbol{i_K}$ such that $\boldsymbol{i_1} < \boldsymbol{i_2} < \cdots < \boldsymbol{i_K}$, the measurement equation for individual $\boldsymbol{n}$ is modelled as an ordered logit model for the latent variable, where parameters $\boldsymbol{\tau}$ are thresholds that need to be estimated:

$$I_{q\ell n} = \begin{cases} i_1 & if \quad -\infty < LV_{qn} \leq \tau_{q\ell 1} \\ i_2 & if \quad \tau_{q\ell 1} < LV_{qn} \leq \tau_{q\ell 2} \\ & \qquad \vdots \\ i_K & if \quad \tau_{q\ell(K-1)} < LV_{qn} < \infty \end{cases}. \tag{6}$$

The latent variables $LV_{1n}, LV_{2n}, \dots, LV_{Qn}$ are linked to the remaining part of the model through a generalisation of the class allocation probabilities π_{n,c_s}, which are now respondent specific by being a function of the latent variable.

The model is finally estimated by maximum simulated likelihood. The estimation involves maximising the joint likelihood of the observed sequence of choices (P_n) and the observed answers to the attitudinal questions ($L_{I_{q\ell n}}$). The two components are conditional on the given realisation of the latent variable LV_{qn}. Accordingly, the log-likelihood function of the model is given by integration over ω_{qn}:

$$LL(\beta, \mu, \gamma, \mu, \zeta, \tau) = \sum_{n=1}^{N} ln \int_{\omega} (P_n \ \prod_{\ell=1}^{L_q} \prod_{q=1}^{Q} L_{I_{q\ell n}}) \ g(\omega) d. \qquad (7)$$

Thus, the joint likelihood function (7) depends on parameters of the utility functions defined in (3), the parameters used in the allocation probabilities, the parameters for the socio-demographic interactions in the latent variable specification defined in (4), and the parameters for the measurement equations defined in (6). Daly et al. (2012) describe different identification procedures. We follow the Bolduc normalisation by setting $\sigma_{\omega} = 1$. All model components are estimated simultaneously and contrasted using PythonBiogeme (Bierlaire, 2003; Bierlaire, 2008) and Ox (Doornik, 2001).

3. Data

The case study focuses on a Basque site of community importance (SCI) known as Garate-Santa Barbara (GSB) which is located in the province of Gipuzkoa, Spain (see Figure 1). It covers around 142ha, mostly private property, distributed between the municipalities of Zarautz and Getaria. GSB was proposed as part of the European Natura 2000 Network (N2K) in 2003 as an SCI (code: ES2120007) taking into account the presence of five environmentally valuable habitats. One year later, it became part of the European list of SCIs and was updated in 2008 (EU Commission, 2004, 2008). GSB-SCI also encompasses a relevant place within the Basque Country's list of highly valuable environmental areas due to the presence of cork oak *(Quercus suber)*. This species is found very rarely in the Basque Country and GSB is the only area in which it can self-regenerate. As well as these environmental values, GSB also has important landscape and recreation values.

One of the key features of the European N2K is that, while not excluding human activities therein, it aims to ensure sustainable future management of the site. This was especially relevant for the GSB site given a potential conflict of land uses: on the one hand, development uses (agricultural development as vineyards or forestry); and, on the other hand, conservation uses (protection of the native cork oak forest, as well as biodiversity conservation). In this context, a valuation survey was conducted in the Basque Country in order to determine the non-market values of the main environmental attributes of GSB N2K site. This would ultimately help policy makers determine a way to design and implement sustainable management plans accounting for both the tangible social costs and the benefits of conserving valuable sites.

The DCE was undertaken following the current state of the art (Hoyos, 2010). Previous studies of the environmental characteristics of GSB, expert advice derived from an interdisciplinary group of researchers that included geographers, biologists, forest managers, agronomists and economists, information derived from in-depth interviews with several key stakeholders (e.g., mayors of the council, the rural development agency, representatives from the regional authority, the Basque Environmental Ministry, Labour Unions, etc.) and the use of focus groups facilitated the definition of environmental attributes and the levels of provision that would be the basis of the DCE. The questionnaire began by describing the actual situation in the natural area, facilitated by the provision of information and pictures. Later in the questionnaire, certain changes in the quality of the site's main attributes were described. It was noted that if the area was not protected, these environmental attributes could suffer different levels of degradation in the future. The hypothesised future land use changes and the proposed protection programmes were found to be both credible and understandable by the focus group participants.

[FIGURE 1]

The information included in the DCE referred to the potential effects of various levels of protection in terms of the following attributes (see Table 2): (1) native forest (NAT) represented by the percentage of land area covered by cork oak woodland (levels ranging 2-30%); (2) percentage of land area covered by vineyards (VIN), levels ranging 10-40%; (3) exotic tree plantations (FOR) represented by land area covered by productive pine forest plantations (levels ranging 15-40%); (4) biodiversity (BIO), based on the number of endangered species of flora and fauna (levels ranging 5-25 species); (5) the level of conservation of recreational and cultural facilities (REC), qualitative level ranging from 'low' to 'very high'; and (6) a cost attribute (COST) regarding the price of the conservation programme (ranging from 0 to 100 euros per capita). These attributes were selected based on focus groups, bio-geographic analysis and external expert advice by key informants.

[TABLE 2]

A main effects fractional factorial design with second order interactions was used to simplify the construction of choice sets (Louviere et al., 2000). The final version of the questionnaire had 120 choice sets (blocked into 20 groups of 6 choice sets); each formed by the status quo option plus two alternative protection programmes for GSB (Programme A and Programme B). For a better understanding of the trade-offs between the attributes and alternatives, the choice sets included maps and percentage values (see Figure 2). The proposed payment vehicle was an annual contribution by all Basque citizens to a foundation exclusively dedicated to protecting the site. The complexity of the choice task was satisfactorily pre-tested in focus groups and through pilot surveys.

[FIGURE 2]

Finally, the survey was administered through in-person computer-aided individual home interviews. The population considered relevant was that of the Basque Autonomous

Community, 1.8 million people aged at least 18. A stratified random sample of 400 individuals was selected from this population. The strata used included age, gender and size of the town of residence, following official statistical information by the Basque Statistics Office (EUSTAT). The questionnaire was distributed using random survey routes in each of the locations in the Basque Country. The data analysis involved 221 completed questionnaires, yielding 1,326 observations, as each respondent was given six choice sets. More detailed information about the environmental characteristics of Garate-Santa Barbara and the survey design can be found in Hoyos et al. (2012).[2]

4. Results and discussion

4.1. Descriptive statistics

Table 3 provides a complete description of the variables used in the econometric models estimation along with their descriptive statistics. The mean age (45.03 years), gender (47% male and 53% female) and disposable income (965 euros) of respondents are in line with the average age, gender and income decomposition of the population (40.15 years, 45% and 1029 euros, respectively). Apart from the six attributes, (native forest (NAT), vineyards (VIN), forest (FOR), biodiversity (BIO), recreation (REC) and cost (COST)), other explanatory variables considered were EUS (taking the value 1 if respondents filled the questionnaire in *euskera*, the Basque language, and 0 otherwise), RECR (taking the value 1 if the respondent was a recreationalist and 0 otherwise) MALE (taking the value 1 if respondent was a male and 0 otherwise), ADULT (the number of adults in the family), CHILD (the number of children in the family), EDUC (for respondent's level of education with 1 being the lowest and 5 the highest), NGO (taking the value 1 if respondent was a member of an environmentalist organisation and 0 otherwise).

[TABLE 3]

[2] A copy of the survey instrument is available from the authors upon request.

In addition to the socioeconomic information, respondents were asked a series of attitudinal questions following the typical AC psychometric scale items shown in Table 1. Table 4 shows the response distributions in a 5-point Likert scale. For each statement, values closer to five would equate to strong agreement while values closer to one would equate to strong disagreement. As shown in this table, respondents are generally aware of the increasing environmental degradation of the Earth and are worried about the environment that future generations will have. For example, 91% of the respondents agreed with Item 1 (environmental protection will provide a better world for me and my children) and 87% disagreed with Item 6 (we do not need to worry much about the environment because future generations will be better able to deal with these problems than wus).

[TABLE 4]

4.2. Exploratory factor analysis

An exploratory factor analysis was conducted on the data, so that the factors considered under the AC scale could be compared with the factors emerging from the data. The exploratory factor analysis employed principal axis factor analysis with promax rotation. The criteria employed to select the number of components to extract from the analysis, were Eigenvalue scores being greater than 0.9, and the percentage of variance explained being smaller than 5%, thus resulting in a four factor solution (see Table 5).

[TABLE 5]

Table 6 presents the rotated component matrix arising from the four factor solution. The four factor solution seems to indicate a clustering of factors close to the structure proposed by Ryan and Spash (2012), as shown in the last column of Table 6. Excepting one item (ACbio2), Factors 1 and 2 correspond to classification of beliefs supporting environmental action (1A and 1B) by these authors, and Factors 3 and 4 correspond to their classification of beliefs supporting environmental inaction (2A and 2B).

[TABLE 6]

4.3. Model specification

As outlined in Section 3, the specification of a hybrid latent class model requires the specification of two types of structural equations, one for the choice model and one for the latent variable model. Following equations (1) and (2), the structural equation for the choice model has a deterministic term V_{int}, defined in our case as:

$$V_{int} = \beta' X_{int} = ASC_i + \beta_{NAT} NAT_{int} + \beta_{VIN} VIN_{int} + \beta_{FOR} FOR_{int} + \beta_{BIO} BIO_{int} + \beta_{REC} REC_{int} + \beta_{COST} COST_{int}, \quad (8)$$

where Nat, Vin, For, Bio, Rec and $Cost$ are the choice attributes described in Table 2. Variable Nat_{int} represents the value of the Nat attribute corresponding to the level for alternative i in choice situation t for respondent n. The remaining attributes are coded according to the levels described in Table 2.

In addition, the structural equation for the q-th latent variable model is given by the following formula:

$$LV_{qn} = \gamma_{q,Eus} Eus_n + \gamma_{q,Recr} Recr_n + \gamma_{q,Male} Male_n + \gamma_{q,Adult} Adult_n + \gamma_{q,Child} Child_n + \gamma_{q,Educ} Educ_n + \gamma_{q,NGO} NGO_n + \omega_{qn} \quad (9)$$

where ω_{qn} is a random disturbance, which is assumed to be normally distributed with a zero mean and standard deviation σ_q. In this application, following the BSEAI framework, we define two latent variables: the first latent variable, LV_{1n}, aims to capture beliefs supporting environmental action, and the second latent variable, LV_{2n}, aims to capture beliefs supporting environmental inaction.

The latent variables, $LV_{1n}$and LV_{1n}, are linked to the remaining part of the model through class allocation probabilities, now becoming respondent-specific and a function of the latent variable, thus:

$$\pi_{n,c_s} = \frac{\exp(\mu_{0s} + \mu_{1s}LV_{1n} + \mu_{2s}LV_{2n} + \lambda_s' SD_n)}{\sum_{s=1}^{C} \exp(\mu_{0s} + \mu_{1s}LV_{1n} + \mu_{2s}LV_{2n} + \lambda_s' SD_n)}, \quad (10)$$

where $\mu_{0s}, \mu_{1s}, \mu_{2s}, and\ \lambda_s'$ are parameters to be estimated. The sign of μ parameters determines whether increases in the value of the latent variable lead to an increased or decreased probability of a specific class allocation function while λ parameters determine the influence of certain sociodemographic characteristics of respondents on the class allocation function. In our case, these sociodemographic variables were *Recr*, *Male*, *Adult*, *Child*, *Educ* and *NGO*.

4.4. Main estimation results

As in the classical LCM framework, the first task when specifying a HLCM is to determine the number of classes. The proper determination of the number of classes in a LCM has been frequently discussed in the applied literature. While it is usually based on goodness of fit indicators such as BIC and AIC (Swait 2007), it has also highlighted the importance of accounting for the significance of parameter estimates as well as its external validity (Scarpa and Thiene, 2011; Hynes et al., 2008).

Table 7 provides goodness of fit indicators together with the number of parameters and class allocation model parameters for the HLCM with two to four classes. This table shows that the BIC and CAIC indicate a solution with two classes, while the AIC favours models with four classes. Given that it seems evident from the literature that the AIC tends to overestimate the number of classes (McLachlan and Peel, 2000) and there is a consensus that parsimony is preferable in modelling, especially in this complicated hybrid framework, goodness of fit criteria would conclude that the best fitting model is a 2-class solution. When looking at significant estimates in the class allocation model, we also find that both latent variables are significant at the 5% significance level. In this empirical application we therefore find that a 2-class solution offers both better model fit as well as consistency with behavioural models.

[TABLE 7]

Table 8 presents estimation results for three models for the BSEAI scale. The first model is a simple MNL model, followed by a LCM (with two classes for comparison purposes), and the HCLM described in the previous section. Focusing first on the MNL model, we find that, consistently with economic theory, the cost coefficient is significantly negative, implying that respondent utility decreases when the cost of a programme increases. Respondent utility increases if the percentage of land area covered by native forest increases and it decreases if the number of endangered species of flora and fauna increases. The remaining attributes are not significant, suggesting that respondents are not sensitive to changes in the levels of these attributes, or that they may cancel each other out due to opposed taste heterogeneity.

[TABLE 8]

The results obtained with the classic LCM specification are similar, in terms of log-likelihood and values of estimated parameters, to those obtained in the HLCM, although it lacks, as it will be later shown, the interpretational power provided by the HLCM. In both cases, the sharp drop in the log-likelihood function clearly favours the LCM specifications over the MNL.

Finally, the estimation results for the HLCM are summarised in Table 9, where estimates are split into four model components: utility functions, latent variables, class allocation probabilities and measurement equations. The parameters of the utility functions for Class 1 show that respondent utility increases if the surface area covered by native forest increases and it decreases if the number of endangered species and the cost of the programme increases. The significant negative coefficient for ASC1 suggests that, everything else being equal, respondents in this class tend to move away from the status quo (i.e. they prefer to implement a protection programme). The parameters for the utility function for Class 2 show that only the cost parameter and the coefficient accompanying the forest attribute are significant, while the remaining parameters are not significant. Accordingly, the utility of the respondents allocated in this class increases when the surface covered by forest tree plantations increases and it decreases when the cost of the programme increases. Comparing both classes, it is important to note that the relative sensitivity to a one per cent increase in the surface covered by native forest, biodiversity protection, the level of conservation of recreation and cultural facilities and to the price coefficient, are higher for Class 1, while sensitivity to increasing the surface covered by tree plantations is higher for Class 2.

[TABLE 9]

The interpretation of the structural equations for the latent variables needs to be combined with the value of the ζ parameters in the measurement equations, because they allow us to understand the sign of the latent variable. All the ζ parameters for the 10 attitudinal questions relating to the first latent variable (i.e. beliefs supportive of environmental action that, for simplicity, we can label as *pro-action)* are negative, thus the more negative the latent variable, the more *pro-action* is the respondent. Conversely, all the ζ parameters for the five attitudinal questions conforming the second latent variable (i.e. beliefs supportive of environmental inaction that, for simplicity, we can label as *pro-inaction)* are positive, thus the more positive the latent variable, the more *pro-inaction* is the respondent. Looking at the γ coefficients for the structural equations, we can see that the latent variable 1 *(pro-action)* is smaller for males and adults and higher for recreationalists and families with children. The latent variable 2 *(pro-inaction)* is higher for males and adults and smaller for families with children, more educated people and environmentalists.

This interpretation is further supported by the positive and highly significant estimates for μ_1 and μ_2 in the class allocation model, which show that respondents with a more negative value for the first latent variable *(pro-action)* are less likely to belong to Class 2, while respondents with a more positive value of the second latent variable *(pro-inaction)* are more likely to belong to Class 2. The reader should bear in mind that, under the latent class modelling framework, respondents have a non-zero probability of belonging to each class and, as a consequence, respondent preferences are a probability weighted mixture of preferences for each of the latent classes. However, to ease the interpretation of the results, we will refer to respondents as more or less likely to belong to a certain class. Allocation to the classes is thus driven by the latent attitudes to a substantial extent, with individuals supporting environmental action more likely to belong to Class 1 and individuals supporting environmental inaction more likely to belong to Class 2. None of the socio-demographic interactions included in the class allocation model were found to be significant. This could be due to the fact that their effect could be better captured in the structural equations for the latent variables.

We can further examine the heterogeneity of respondents by characterising the likelihood of different individuals belonging to each class. If we take into account both the estimated class allocation probabilities for each respondent and the values of the relevant explanatory variables, it is possible to find an expected value for selected variables in each class. For example, the expected value for the male dummy in Class 1 can be computed as:

$$male_{nc_1} = \frac{\sum_{n=1}^{N}(\pi_{n1} \cdot male_n)}{\sum_{n=1}^{N}(\pi_{n1})}, \tag{11}$$

where *N* denotes the number of respondents, $male_n$ is 1 if the *n*-th respondent is male and 0 otherwise, and π_{n1} is the probability of the respondent *n* falling into Class 1, computed on the basis of the class allocation model.

The above estimates can be calculated using prior or posterior allocation probabilities. Following Equation (10), we can compute the prior estimates of the class probabilities, $\hat{\pi}_{n,c_s}$, by substituting the μ parameters by their corresponding estimated value. These class allocation probabilities are respondent specific and they are a function of the latent variables, LV_{qn}, which, at the same time, depends on the random error term, meaning that the allocation probabilities themselves follow a random distribution. Following Equation (3), the posterior estimates of the latent class probabilities can be computed as:

$$\hat{\pi}_{c_s|n} = \frac{\widehat{\Pr}(y_n^t|c_s) \cdot \hat{\pi}_{n,c_s}}{\sum_{s=1}^{c} \widehat{\Pr}(y_n^t|c_s) \cdot \hat{\pi}_{n,c_s}} \tag{12}$$

We therefore simulate the prior and posterior probabilities in (16) using 10,000 draws from the latent variables of each respondent.

[TABLE 10]

Table 10 shows the differences in the expected values of the explanatory variables in a class that can help to characterise each class. In the first class we find a higher presence of Basques, recreationalists, females, children and environmentalists, while the second class is mainly characterised by a higher presence of males, adults and higher education levels. This characterisation reflects the effect that latent attitudes have on class allocation probabilities, where individuals supporting environmental action are more likely to be in Class 1. We also found that around 80% of the population of the Basque Country belongs to this category, thus supporting environmental action. These results are in line with those found in other valuation studies in the region (Hoyos et al., 2009; Longo et al., 2012). The computation of posterior probabilities shifts this distribution slightly, with around 85% of the population belonging to Class 1.

4.5. Welfare measures

We next turn our attention to the computation of welfare measures using the HLCM estimates. Willingness-to-pay (WTP) estimates provide us with the implied monetary valuation of different changes in attribute levels: a positive WTP estimate would show the amount of money that respondents would be willing to pay for a marginal change in the levels of a given attribute, whereas a negative WTP would show the amount of money that respondents would be willing to pay to prevent that change.

Table 11 shows the mean marginal WTP measures corresponding to significant attributes in the two classes. Respondents belonging to Class 1 (which we have previously characterised as individuals more likely to support environmental action) are WTP 3.07 euros per year for a 1% increase in the land area covered by native forest, and 3.21 euros to prevent an increase in the number of endangered species. Conversely, the only significant attribute for Class 2 is exotic tree plantations (FOR), suggesting the individuals belonging to this class are WTP 0.86 euros per year for a 1% increase in the land area covered by exotic tree plantations. As a consequence, respondents belonging to this class (which we have previously characterised as individuals more likely to support environmental inaction), show a higher concern for the development of productive activities.

[TABLE 11]

Next, we simulate the WTP values for the sample population of respondents computed as a weighted mean of the WTP values in each of the two classes. That is, for example, for the native forest (NAT) attribute, the corresponding value for respondent n is

$$WTP_n = \pi_{n,c_1}\left(-\frac{\beta_{NAT}^{c1}}{\beta_{COST}^{c1}}\right) + \pi_{n,c_2}\left(-\frac{\beta_{NAT}^{c2}}{\beta_{COST}^{c2}}\right). \tag{13}$$

We compute the WTP estimates using both prior (Table 12) and posterior allocation probabilities (Table 13) and for different subgroups of individuals according to gender, their recreational activities and whether they have children. The results are similar although, coherently with the change in the class allocation probabilities, slightly higher when accounting for posterior probabilities. They show that as we move from no-recreationalist males without children towards recreationalist-females with children, WTP to protect natural resources, (native forest (NAT) and biodiversity (BIO)), increases and WTP for more productive activities, such as exotic tree plantation decreases.

Previous research into respondent characteristics influencing WTP measures has given similar results. A previous choice experiment conducted in the same region found that recreationalists and families with children had a higher WTP to protect natural resources (Hoyos et al., 2009). Gender and children's effects have also been commonly found in the literature (see, for example, Dupont (2004) or Luchs and Mooradian (2012).

[TABLES 12 AND 13]

5. Discussion and Conclusions

Environmental economists are increasingly interested in better understanding how people cognitively organise their beliefs and attitudes towards environmental change in order to identify key motives and barriers that stimulate or prevent action. This paper has explored the utility of a commonly used psychometric scale, the awareness of consequences scale, in order to explain stated choices in the context of a DCE.[3] Contrary to many previous studies, environmental attitudes have not been directly incorporated as explanatory variables but as latent variables using a hybrid choice modelling framework. This novel approach has been applied to a DCE conducted in the Basque Country (Spain) in 2008 aimed at valuing land-use policies in a Natura 2000 Network site.

It is common to measure environmental attitudes using scales, and the AC scale is one of the most widely used examples. Given the empirical limitations often found in the classical interpretation of the AC scale items (e.g. Snelgar, 2006), environmental attitudes are incorporated using the BSEAI perspective recently proposed by Ryan and Spash (2012).

The empirical analysis of stated choices shows that respondents have an unobserved underlying attitude towards the environmental attributes, explaining both the stated choices and the responses to the attitudinal questions. The HLCM allows us two distinguish two qualitatively different classes: respondents belonging to Class 1 (80-85% of the sample population) show a higher sensitivity to environmental attributes (native forest, biodiversity and recreation); in the second class, where 15-20% of the sample population is probabilistically allocated, respondents show a higher sensitivity to agricultural development attributes such as forest tree plantation extensions. Allocation to classes is, to a substantial extent, driven by latent attitudes, with individuals supporting environmental action more likely to belong to Class 1 and individuals supporting environmental inaction more likely to belong to Class 2. Structural equations for the latent variables allow us to further examine the heterogeneity of respondents, finding that Basques, recreationalists, females, families with children and environmentalists are more likely to belong to Class 1, and males, adults and higher educated people more likely to belong to Class 2. In line with these findings, welfare measure analysis

[3] Interested readers may find a review of the use of the AC scale in environmental valuation in Spash (2006).

shows that, as we move from no-recreationalist males without children towards recreationalist-females with children, the WTP to protect natural resources (NAT and BIO) increases and the WTP for agricultural development activities, such as exotic tree plantations, decreases.

These results have important policy implications. There is a wide consensus among social scientists that confronting the increasing threat to the welfare of human civilisation imposed by environmental issues requires, among other things, behavioural changes by citizens, governments and companies. The results found in this paper suggest that, in general, more effective environmental policies can be designed if targeted to females, people with children and recreationalists. On the other hand, males and families without children may require specific environmental education in order to increase their awareness about environmental problems and to identify the barriers that they seem to have preventing environmental action. Further research is needed in order to investigate whether these results can be extrapolated to other regions and countries as well as determine the best procedures, both for collecting attitudinal information, and incorporating it in the analysis of discrete choices.

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Table 1: Beliefs supportive of environmental action and inaction (BSEAI scale)

Group 1A	*Beliefs that environmental protection has positive consequences*
EGO1	Environmental protection will provide a better world for me and my children
EGO2	Environmental protection is beneficial to my health
EGO5	A clean environment provides me with better opportunities for recreation
ALT1	Environmental protection benefits everyone
ALT2	Environmental protection will help people have a better quality of life
BIO4	Tropical rain forests are essential to maintaining a healthy planet Earth
Group 1B	*Beliefs that the environment is being seriously harmed*
ALT4	The effects of pollution on public health are worse than we realise
ALT5	Pollution generated here harms people all over the Earth
BIO2	Over the next several decades, thousands of species will become extinct
BIO5	Modern development threatens wildlife
Group 2A	*Beliefs that environmental protection has negative consequences*
EGO3	Protecting the environment will threaten jobs for people like me
EGO4	Laws to protect the environment limit my choice and personal freedom
Group 2B	*Beliefs that the environment is not being seriously harmed*
ALT3	We do not need to worry much about the environment because future generations will be better able to deal with these problems than us
BIO1	While some local plants and animals may have been harmed by environmental degradation, over the whole Earth there has been little effect
BIO3	Claims that current levels of pollution are changing earth's climate are exaggerated

Table 2: Attributes and levels considered

Attribute	Level					
Native forest (NAT)	2%*	10%	20%	30%		
Vineyard (VIN)	40%*	30%	20%	10%		
Exotic tree plantations (FOR)	40%*	30%	25%	15%		
Biodiversity (BIO)	25*	15	10	5		
Recreation (REC)	Low*	Medium	High	Very High		
Cost of programme (COST)	0€*	5€	10€	30€	50€	100€

(*) Levels with asterisks represent the status quo scenario.

Table 3: Summary statistics and socioeconomic variables

Variable	Description	Mean	Std.Dev.	Min	Max
NAT	Native forest attribute	14.13	10.87	2	30
VIN	Vineyard attribute	26.79	11.46	10	40
FOR	Forest attribute	28.90	9.39	15	40
BIO	Biodiversity attribute	15.02	7.80	5	25
REC	Recreation attribute	-0.34	2.31	-3	3
COST	Cost	26.22	33.91	0	100
EUS	Basque language	0.07	0.26	0	1
MALE	Gender (1 if male)	0.47	0.50	0	1
ADULT	Number adults	2.56	0.92	1	5
CHILD	Number children	0.31	0.66	0	4
EDUC	Education	2.73	1.16	1	5
NGO	Environmental NGO	0.03	0.16	0	1
RECR	Recreationalist	0.50	0.50	0	1
AGE	Age	45.04	18.73	18	89
INC	Personal income	965.00	1018.45	0	8000
FINC	Family income	2051.55	1193.93	0	8000

Table 4: Responses to the environmental attitudinal questions

AC scale	1	2	3	4	5
Group 1A	*Beliefs that environmental protection has positive consequences*				
EGO1	0.45%	0.45%	7.69%	28.96%	62.44%
EGO2	0.90%	l0.90%	7.24%	26.24%	64.71%
EGO5	0.45%	2.26%	9.05%	32.13%	56.11%
ALT1	0.00%	1.81%	5.43%	28.51%	64.25%
ALT2	0.45%	2.71%	9.50%	28.05%	59.28%
BIO4	1.36%	2.26%	12.67%	29.86%	53.85%
Group 1B	*Beliefs that the environment is being seriously harmed*				
ALT4	1.36%	4.52%	15.84%	33.94%	44.34%
ALT5	4.52%	7.69%	20.81%	35.75%	31.22%
BIO2	4.98%	3.17%	15.38%	33.94%	42.53%
BIO5	3.17%	1.81%	14.48%	36.20%	44.34%
Group 2A	*Beliefs that environmental protection has negative consequences*				
EGO3	56.56%	14.93%	11.76%	10.86%	5.88%
EGO4	46.61%	28.05%	16.29%	7.69%	1.36%
Group 2B	*Beliefs that the environment is not being seriously harmed*				
ALT3	62.90%	23.98%	7.24%	4.07%	1.81%
BIO1	35.75%	32.13%	18.10%	11.31%	2.71%
BIO3	35.29%	23.08%	22.62%	14.03%	4.98%

Table 5: Eigenvalues and percentage of variance explained

Factors	Total	% of variance	Cumulative %
Factor 1	2.68	17.90%	17.90%
Factor 2	1.24	8.30%	26.10%
Factor 3	1.02	6.80%	32.90%
Factor 4	0.95	6.30%	39.20%

Table 6: Factor loadings

AC item	Factor 1	Factor 2	Factor 3	Factor 4	BSEAI
ACalt1	**0.78**				1A
ACego5	**0.76**		0.11		1A
ACego2	**0.64**			0.37	1A
ACalt2	**0.63**			0.3	1A
ACego1	**0.42**		-0.16	0.17	1A
ACbio4	**0.39**	0.2	-0.24	-0.23	1A
ACalt4	**0.49**			0.3	1B
ACalt5	**0.31**	0.16		0.1	1B
ACbio2		0.11		**0.34**	1B
ACbio5		**1.04**	0.11	0.14	1B
ACego3		0.13	0.21	**-0.33**	2A
ACego4				**-0.25**	2A
ACbio3	0.13	0.13	**0.81**		2B
ACbio1		-0.17	**0.41**	-0.22	2B
ACalt3				**-0.42**	2B

The factor loadings in bold are generally the highest in each column.

Table 7: Goodness of fit criteria for HLCM with different numbers of classes

	2 Classes		*3 Classes*		*4 Classes*	
Log likelihood		-4265.2		-4205.9		-4172.4
Number of parameters		113		130		147
N		1326		1326		1326
AIC		8756.3		8671.9		**8638.9**
BIC		**9342.8**		9346.5		9401.8
CAIC		**9455.8**		9476.5		9548.8
Class 2	***coeff.***	***p-value***	***coeff.***	***p-value***	***coeff.***	***p-value***
μ_{02}	-2.400 ***	0.00	-0.177	0.86	-0.271	0.81
μ_{12}	0.703 **	0.01	0.357	0.23	0.699 *	0.05
μ_{22}	0.649 *	0.05	0.356	0.38	0.699	0.20
$\lambda_{12,Recr}$	-0.551	0.21	-0.783	0.12	0.232	0.74
$\lambda_{22,Male}$	-0.180	0.70	-0.219	0.70	-0.395	0.57
$\lambda_{32,Adult}$	0.0958	0.66	0.021	0.93	-0.254	0.43
$\lambda_{42,Child}$	0.436	0.19	0.404	0.52	32.700	0.39
$\lambda_{52,Educ}$	0.214	0.22	-0.014	0.95	0.009	0.97
$\lambda_{62,NGO}$	0.892	0.50	0.744	0.57	-0.244	0.82
Class 3			***coeff.***	***p-value***	***coeff.***	***p-value***
μ_{03}			2.290 **	0.01	-3.590 *	0.06
μ_{13}			-0.346	0.16	1.120 **	0.02
μ_{23}			-0.318	0.37	1.200 *	0.10
$\lambda_{13,Recr}$			-0.315	0.48	-0.067	0.95
$\lambda_{23,Male}$			0.040	0.94	-0.424	0.59
$\lambda_{33,Adult}$			-0.145	0.48	0.277	0.52
$\lambda_{43,Child}$			0.140	0.82	34.100	0.37
$\lambda_{53,Educ}$			-0.260	0.17	0.188	0.58
$\lambda_{63,NGO}$			-0.528	0.71	-28.200	1.00
Class 4					***coeff.***	***p-value***
μ_{04}					1.760 *	0.08
μ_{14}					0.007	0.98
μ_{24}					0.197	0.71
$\lambda_{14,Recr}$					0.485	0.47
$\lambda_{24,Male}$					-0.256	0.66
$\lambda_{34,Adult}$					-0.238	0.39
$\lambda_{44,Child}$					32.900	0.39
$\lambda_{54,Educ}$					-0.219	0.30
$\lambda_{64,NGO}$					-1.670	0.32

Table 8: MNL, LCM and HCLM estimated models

	MNL		LCM				HLCM			
Number of individuals:	221		221				221			
Number of observations:	1326		1326				1326			
Log-likelihood:	-1208.705		-902.60				-4265.168			
Parameters:	8		23				113			
			Class 1		*Class 2*		*Class 1*		*Class 2*	
	est.	*p-val.*	est.	*p-val.*	est.	*p-val.*	est.	*p-val.*	est.	*p-val.*
ASC_1	0.266	0.30	-1.550 ***	0.00	-0.896	0.35	-1.960 ***	0.00	-0.447	0.64
ASC_2	0.094	0.17	0.085	0.30	0.540 *	0.07	0.086	0.30	0.438 *	0.08
β_{NAT}	0.046 ***	0.00	0.052 ***	0.00	0.025	0.13	0.053 ***	0.00	0.021	0.11
β_{VIN}	0.007	0.12	0.007	0.23	0.016	0.39	0.006	0.28	0.019	0.20
β_{FOR}	-0.007	0.27	-0.011	0.13	0.067 ***	0.00	-0.010	0.14	0.048 **	0.04
β_{BIO}	-0.043 ***	0.00	-0.053 ***	0.00	0.015	0.66	-0.056 ***	0.00	0.016	0.61
β_{REC}	0.015	0.52	0.033	0.20	-0.124	0.12	0.032	0.22	-0.082	0.26
β_{COST}	-0.017 ***	0.00	-0.017 ***	0.00	-0.095 ***	0.00	-0.017 ***	0.00	-0.055 ***	0.01

Class allocation model (LCM)	est.	*p-val.*	*Class allocation model* (HLCM)	est.	*p-val.*
μ_{02}	-2.280 ***	0	μ_{02}	-2.400 ***	0.00
μ_{12}			μ_{12}	0.703 ***	0.01
μ_{22}			μ_{22}	0.649 **	0.05
$\lambda_{12,Recr}$	-0.702 *	0.06	$\lambda_{12,Recr}$	-0.551	0.21
$\lambda_{22,Male}$	0.402	0.27	$\lambda_{22,Male}$	-0.180	0.70
$\lambda_{32,Adult}$	0.325 *	0.08	$\lambda_{32,Adult}$	0.068	0.66
$\lambda_{42,Child}$	0.008	0.97	$\lambda_{42,Child}$	0.436	0.19

$\lambda_{52,Educ}$	0.093	0.55	$\lambda_{52,Educ}$	0.214	0.22
$\lambda_{62,NGO}$	-0.049	0.97	$\lambda_{62,NGO}$	0.892	0.50

Table 9: HLCM estimation results: structural and measurement equations

Number of individuals:	1326
Number of observations:	221
Log-likelihood:	-4268.06

Utility functions

	est.	p-value
$ASC_{1,Cl1}$	-1.960 ***	0.00
$ASC_{2,Cl1}$	0.086	0.30
$\beta_{NAT,Cl1}$	0.053 ***	0.00
$\beta_{VIN,Cl1}$	0.006	0.28
$\beta_{FOR,Cl1}$	-0.010	0.14
$\beta_{BIO,Cl1}$	-0.056 ***	0.00
$\beta_{REC,Cl1}$	0.032	0.22
$\beta_{COST,Cl1}$	-0.017 ***	0.00
$ASC_{1,Cl2}$	-0.447	0.64
$ASC_{2,Cl2}$	0.438 *	0.08
$\beta_{NAT,Cl2}$	0.021	0.11
$\beta_{VIN,Cl2}$	0.019	0.20
$\beta_{FOR,Cl2}$	0.047 **	0.04
$\beta_{BIO,Cl2}$	0.015	0.61
$\beta_{REC,Cl2}$	-0.082	0.26
$\beta_{COST,Cl2}$	-0.055 ***	0.01

Measurement eq. (thresholds and const.)

	est.	p-value
$\tau_{1,1,1}$	-7.040 ***	0.00
$\delta_{1,1,1}$	0.699	0.33
$\delta_{1,1,2}$	2.540 ***	0.00
$\delta_{1,1,3}$	2.600 ***	0.00
$\tau_{1,2,1}$	-10.000 ***	0.00
$\delta_{1,2,1}$	2.280 **	0.04
$\delta_{1,2,2}$	2.260 ***	0.00
$\delta_{1,2,3}$	3.600 ***	0.00
$\tau_{1,3,1}$	-8.940 ***	0.00
$\delta_{1,3,1}$	0.869	0.17
$\delta_{1,3,2}$	2.330 ***	0.00
$\delta_{1,3,3}$	3.360 ***	0.00
$\tau_{1,4,1}$	-7.500 ***	0.00
$\delta_{1,4,1}$	1.930 **	0.03
$\delta_{1,4,2}$	1.830 ***	0.00
$\delta_{1,4,3}$	2.820 ***	0.00
$\tau_{1,5,1}$	-5.390 ***	0.00
$\delta_{1,5,1}$	1.010 **	0.03

Measurement eq. (effects of LVs)

	est.	p-value
$\zeta_{1,1}$	-1.810 ***	0.00
$\zeta_{1,2}$	-3.590 ***	0.00
$\zeta_{1,3}$	-3.340 ***	0.00
$\zeta_{1,4}$	-2.130 ***	0.00
$\zeta_{1,5}$	-1.440 ***	0.00
$\zeta_{1,6}$	-3.460 ***	0.00
$\zeta_{1,7}$	-0.700 ***	0.00
$\zeta_{1,8}$	-1.860 ***	0.00
$\zeta_{1,9}$	-1.150 ***	0.00
$\zeta_{1,10}$	-1.150 ***	0.00
$\zeta_{2,1}$	0.643 ***	0.00
$\zeta_{2,2}$	0.993 ***	0.00
$\zeta_{2,3}$	1.220 ***	0.00
$\zeta_{2,4}$	1.170 ***	0.00
$\zeta_{2,5}$	0.936 ***	0.00

Latent variables specification		

Structural eq. for LV1 (pro-action)

	est.	*p-value*
$\gamma_{1,Eus}$	0.251	0.33
$\gamma_{1,Recr}$	-0.433	0.02
$\gamma_{1,Male}$	0.396	0.03
$\gamma_{1,Adult}$	0.145	0.02
$\gamma_{1,Child}$	-0.292	0.01
$\gamma_{1,Educ}$	-0.041	0.44
$\gamma_{1,NGO}$	-0.476	0.51

Structural eq. for LV2 (inaction)

	est.	*p-value*
$\gamma_{2,Eus}$	0.291	0.49
$\gamma_{2,Recr}$	-0.194	0.31
$\gamma_{2,Male}$	0.607	0.00
$\gamma_{2,Adult}$	0.226	0.06
$\gamma_{2,Child}$	-0.389	0.02
$\gamma_{2,Educ}$	-0.147	0.06
$\gamma_{2,NGO}$	-0.849	0.10

Class allocation probabilities

	est.	*p-value*
μ_{02}	-2.400 ***	0.00

$\delta_{1,5,2}$	1.770 ***	0.00
$\delta_{1,5,3}$	2.040 ***	0.00
$\tau_{1,6,1}$	-8.250 ***	0.00
$\delta_{1,6,1}$	1.900 ***	0.00
$\delta_{1,6,2}$	4.000 ***	0.00
$\tau_{1,7,1}$	-3.320 ***	0.00
$\delta_{1,7,1}$	0.523 **	0.01
$\delta_{1,7,2}$	1.280 ***	0.00
$\delta_{1,7,3}$	1.680 ***	0.00
$\tau_{1,8,1}$	-5.970 ***	0.00
$\delta_{1,8,1}$	1.650 ***	0.00
$\delta_{1,8,2}$	1.850 ***	0.00
$\delta_{1,8,3}$	2.460 ***	0.00
$\tau_{1,9,1}$	-3.820 ***	0.00
$\delta_{1,9,1}$	1.140 ***	0.00
$\delta_{1,9,2}$	1.460 ***	0.00
$\delta_{9,3}$	2.010 ***	0.00
$\tau_{1,10,1}$	-4.190 ***	0.00
$\delta_{1,10,1}$	0.473 **	0.04
$\delta_{1,10,2}$	1.600 ***	0.00
$\delta_{1,10,3}$	2.110 ***	0.00
$\tau_{2,1,1}$	0.032	0.90
$\delta_{2,1,1}$	1.350 ***	0.00
$\delta_{2,1,2}$	1.300 ***	0.00
$\delta_{2,1,3}$	2.020 ***	0.00
$\tau_{2,2,1}$	0.584	0.14
$\delta_{2,2,1}$	0.830 ***	0.00
$\delta_{2,2,2}$	0.832 ***	0.00

μ_{12}	0.703 ***	0.01	$\delta_{2,2,3}$	1.290 ***	0.00
μ_{22}	0.649 **	0.05	$\tau_{2,3,1}$	1.030 **	0.02
$\lambda_{12,Recr}$	-0.551	0.21	$\delta_{2,3,1}$	1.740 ***	0.00
$\lambda_{22,Male}$	-0.180	0.70	$\delta_{2,3,2}$	1.050 ***	0.00
$\lambda_{32,Adult}$	0.095	0.66	$\delta_{2,3,3}$	1.320 **	0.01
$\lambda_{42,Child}$	0.436	0.19	$\tau_{2,4,1}$	-0.488	0.25
$\lambda_{52,Educ}$	0.214	0.22	$\delta_{2,4,1}$	1.760 ***	0.00
$\lambda_{62,NGO}$	0.892	0.50	$\delta_{2,4,2}$	1.360 ***	0.00
			$\delta_{2,4,3}$	2.010 ***	0.00
			$\tau_{2,5,1}$	-0.497	0.17
			$\delta_{2,5,1}$	1.200 ***	0.00
			$\delta_{2,5,2}$	1.350 ***	0.00
			$\delta_{2,5,3}$	1.610 ***	0.00

Note: The absence of one threshold for indicator 6 is due to the fact that none of the respondents chose one level of the *Likert* scale. In practice, each $\boldsymbol{\tau}_{\boldsymbol{q\ell 2}}, \dots, \boldsymbol{\tau}_{\boldsymbol{q\ell K-1}}$ is estimated using a set of auxiliary parameters $\boldsymbol{\delta}_{\boldsymbol{q\ell 2}}, \dots, \boldsymbol{\delta}_{\boldsymbol{q\ell(K-2)}}$ such that $\boldsymbol{\tau}_{\boldsymbol{q\ell 2}} = \boldsymbol{\tau}_{\boldsymbol{q\ell 1}} + \boldsymbol{\delta}_{\boldsymbol{q\ell 2}}, \boldsymbol{\tau}_{\boldsymbol{q\ell 3}} = \boldsymbol{\tau}_{\boldsymbol{q\ell 2}} + \boldsymbol{\delta}_{\boldsymbol{q\ell 3}}, \dots$

Table 10: Expected values for explanatory variables in latent classes and coefficients in allocation functions

Expected values for explanatory variables			*Coefficients in allocation functions*	
	Class 1	*Class 2*	*Class 1*	*Class 2*
Basque language (EUS)	0.086	0.038	*n.s.*	*n.s.*
Recreationalist (RECR)	0.537	0.417	-0.433	*n.s.*
Male (MALE)	0.449	0.507	0.396	0.607
Number of adults (ADULT)	2.475	2.776	0.145	0.226
Number of children (CHILD)	0.333	0.245	-0.292	-0.389
Education (EDUC)	2.697	2.824	*n.s.*	-0.147
NGO (NGO)	0.031	0.017	*n.s.*	-0.849

Table 11: Mean marginal WTP estimates by classes

	Class 1	Class 2
Native Forest (NAT)	*3.07*	*n.s.*
Vineyards (VIN)	*n.s.*	*n.s.*
Exotic tree plantations (FOR)	*n.s.*	*0.86*
Biodiversity (BIO)	*-3.21*	*n.s.*
Recreation (REC)	*n.s.*	*n.s.*

Table 12: Simulated WTP values for different socio-demographic groups (using prior probabilities)

			NAT		FOR		BIO	
MALE	**RECR**	**CHILD**	**median**	**90% C.I.**	**median**	**90% C.I.**	**median**	**90% C.I.**
Yes	No	No	2.16	(1.03,2.79)	0.26	(0.08,0.58)	-2.26	(-2.92,-1.08)
Yes	No	Yes	2.25	(1.26,2.82)	0.23	(0.07,0.51)	-2.36	(-2.96,-1.32)
Yes	Yes	No	2.61	(1.49,2.95)	0.13	(0.03,0.44)	-2.73	(-3.09,-1.57)
Yes	Yes	Yes	2.63	(2.03,2.93)	0.12	(0.04,0.29)	-2.76	(-3.08,-2.12)
No	No	No	2.41	(1.34,2.90)	0.18	(0.05,0.49)	-2.53	(-3.04,-1.40)
No	No	Yes	2.34	(1.51,2.88)	0.20	(0.05,0.44)	-2.46	(-3.02,-1.58)
No	Yes	No	2.74	(1.85,2.99)	0.09	(0.02,0.34)	-2.88	(-3.15,-1.94)
No	Yes	Yes	2.81	(2.15,3.00)	0.07	(0.02,0.26)	-2.94	(-3.15,-2.26)
Median marginal WTP			***2.52***	***(1.38,2.96)***	***0.15***	***(0.03,0.47)***	***-2.64***	***(-3.10,-1.44)***

Table 13: Simulated WTP values for different socio-demographic groups (using posterior probabilities)

			NAT		FOR		BIO	
MALE	**RECR**	**CHILD**	**median**	**90% C.I.**	**median**	**90% C.I.**	**median**	**90% C.I.**
Yes	No	No	2.24	(0.00,3.07)	0.23	(0.00,0.86)	-2.34	(-3.21,0.00)
Yes	No	Yes	2.92	(0.00,3.07)	0.04	(0.00,0.86)	-3.06	(-3.22,0.00)
Yes	Yes	No	3.03	(0.00,3.07)	0.01	(0.00,0.86)	-3.18	(-3.21,0.00)
Yes	Yes	Yes	3.07	(0.00,3.07)	0.00	(0.00,0.86)	-3.21	(-3.22,0.00)
No	No	No	3.01	(0.00,3.07)	0.01	(0.00,0.86)	-3.16	(-3.22,0.00)
No	No	Yes	3.04	(0.00,3.07)	0.00	(0.00,0.86)	-3.19	(-3.22,0.00)
No	Yes	No	3.03	(0.00,3.07)	0.01	(0.00,0.86)	-3.18	(-3.22,0.00)
No	Yes	Yes	3.07	(0.00,3.07)	0.00	(0.00,0.86)	-3.22	(-3.22,0.00)
Median marginal WTP			***3.02***	***(0.00,3.07)***	***0.01***	***(0.00,0.86)***	***-3.17***	***(-3.22,0.00)***

Figure 1: Location Garate-Santa Barbara N2000 site (Basque Country-Southern Europe).

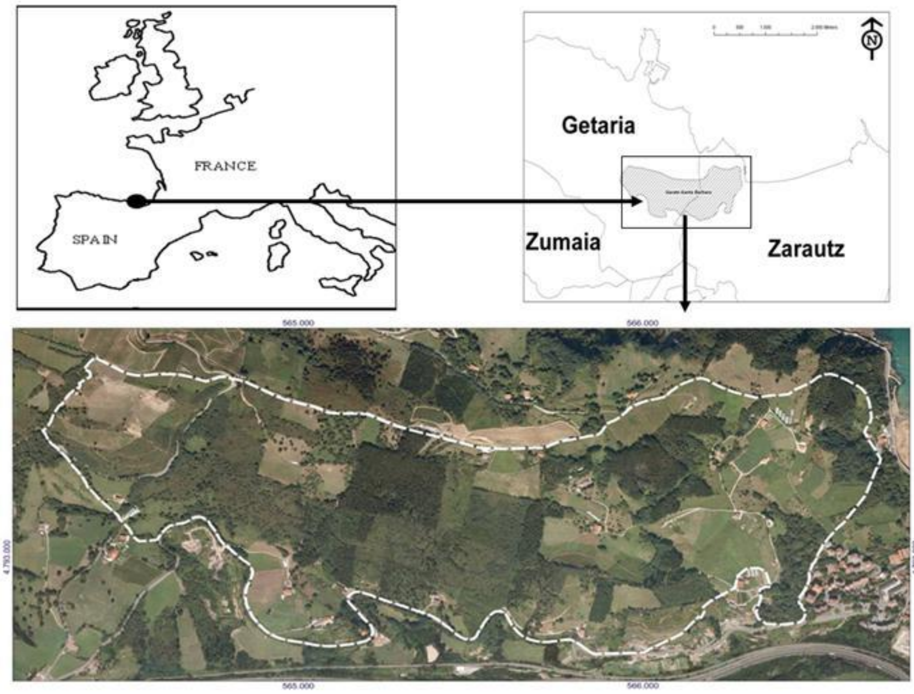

Figure 2: Example of a choice set with different protection alternatives used in the valuation exercise, translated into English.