Societal preferences for the conservation of traditional pig breeds and their agroecosystems: Addressing preference heterogeneity and protest responses through deterministic allocation and scale-extended models

Elsa Varela[1,2*], Zein Kallas[1]

[1] CREDA-UPC-IRTA. Center for Agro-Food Economy and Development. Parc Mediterrani de la Tecnologia, Edifici ESAB. C/ Esteve Terrades, 8. E-08860 Castelldefels (Barcelona), Spain.

[2] IRTA. Catalan Institute of Agrifood Research and Technology. Caldes de Montbui (Barcelona), Spain. E- 08140

[*] Corresponding author email: elsa.varela@irta.cat/elsa.varela@upc.edu Phone: +34 935153206

ABSTRACT

This study assesses preferences of local dwellers on the island of Majorca (Spain) for the conservation the traditional, extensively reared Majorcan Black Pig and its linked agroecosystem. A choice experiment study was conducted with equal sample weight between rural and urban dwellers. Protest responses in this study amount up to 35% of the sample. The widespread procedure of removing these responses from the ulterior analysis, may lead to sample selection bias. Alternative discrete modelling approaches are tested keeping these observations in the sample. Latent class analysis was conducted, and protest responses (35%) were either allowed to free allocate or deterministically allocated to one preference class. Additionally, scale-adjusted latent class models were also estimated for both approaches.

Free allocated models report better information criteria estimates but may lead to inaccurate interpretation of results due to preventing segregation into real preference groups. The best model in terms of performance and interpretability is a 3-class model where protest responses are deterministically allocated to one class and random parameters are included to account for heterogeneity. Among the non-protesting classes, we find heterogeneous preferences where 40% of the respondents are mostly concerned with management and product innovation and the remainder 24% more breed-concerned respondents favour price increases in breed-based products to fund the improvement of the agroecosystem.

Keywords: Scale-adjusted latent class model, random parameter latent class model, protesters, extensive systems, animal genetic diversity

1 Introduction

Extensive outdoor low-intensity livestock farming systems are the principal form of management of high natural value farmland in Europe and able to satisfy demands for public goods such as landscapes and biodiversity (Beaufoy y Cooper, 2008). However, the opportunity costs associated with this form of land management and the insufficient recognition in markets and policies can ultimately risk the future of sustainable farming (Swinton et al., 2007), propelling these farmers towards restructuring to achieve either more profitable forms of land use or land abandonment (Cooper et al., 2009). Although grazing land intensity has declined across most of Europe (Pe'er et al., 2017), the decrease in the number of livestock units is higher than the decrease in the total number of farms with an intensification pattern (Agrosynergie 2011), and this phenomenon is a consequence of the need to increase productivity to pay for increasing costs and the gradual decrease in the prices of agricultural products (Aparicio Tovar y Vargas Giraldo, 2006). Furthermore, evidence suggests that the Common Agricultural Policy (CAP) significantly contributed to this process, linked among other factors to the decoupling payments (Pe'er et al., 2017, 2014). This contrasts with the increasing societal concerns about the carbon footprint, industrialisation of agriculture, fair trade, food security, or animal welfare (Bernués et al., 2011).

Extensive farming systems are tightly linked to domestic animal diversity, that is, animal genetic resources (AnGRs) adapted to their local conditions and over thousands of years of domestication (Anderson, 2003). The conservation of farmland biodiversity and more specifically of AnGR accrue a series of private and public value components (Tisdell, 2003). The role of AnGR in supporting agroecosystem resilience (Hajjar et al., 2008) is maintaining socio-cultural traditions, local identities, and traditional knowledge (Gandini y Villa, 2003; Nautiyal et al., 2008); gene flow global option values (e.g. Bellon, 2009), cultural landscapes (Tisdell, 2003), and shares the characteristics of public goods (Fisher y Kerry Turner, 2008); and a high degree of non-excludability (Narloch et al., 2011). Not accounting for these non-market values (e.g. future option values or socio-cultural values) that society holds for these traditional breeds has produced an overestimation of the performance of improved AnGR. Because rearing these traditional breeds is many times not profitable under present market conditions, compensation payments are necessary to make these populations viable (Zander y Drucker, 2008).

Traditional high-quality meat products from Mediterranean pigs are produced in extensive-type production systems that use native agro-sylvo-pastoral resources. This case applies to the Majorcan Black Pig (MBP), a traditional, extensive pig breed native to Mallorca island (Balearic Islands, Spain), characterised by its high rusticity and adaptation to Mediterranean climatic conditions (Gonzalez et al., 2013; Tibau et al., 2019). In 1997, the Spanish Ministry of Agriculture has catalogued the MBP as a breed of special protection in danger of extinction.

In this study, we assessed Majorca island dwellers' preferences for management options for the MBP and its agroecosystem and related products through a choice experiment survey. These options may align with thriving strategies followed by extensive farming systems and policy schemes to support these systems. Investigating the preference heterogeneity of citizens has been recognised as a useful tool for policymakers to design better policy actions, especially reaching specific segments of the target population and accounting for winners and losers in proposed policy actions (Thiene et al., 2015). Furthermore, we explored the performance of modelling approaches where we control for differences in error variance across respondents by applying scale-adjusted latent class (SALC) models (Magidson and Vermunt,2007).

2 Case study description

Land use on the island of Mallorca is similar to other areas in the Mediterranean where land use intensification through urban sprawl, increases in tourism, and abandonment of rainfed arboriculture and spontaneous reforestation have occurred (Marull et al., 2015). These changes have produced a loss in the heterogeneous, well-connected land use mosaics with a positive interplay between the intermediate level of farming disturbances and land cover complexity endowed with a rich biocultural heritage that are able to preserve a wildlife-friendly agroecological matrix likely to house high biodiversity (Marull et al., 2015).

The MBP had great importance in the economy and in the Majorcan lifestyle until the mid-twentieth century and contributed to the cultural heritage of the island (Tibau et al., 2019) because of its high adaptation to the local environment and ability to exploit the scarce natural resources of the island (Jaume y Alfonso, 2000). Traditional MBP farms were mixed farms, that is, a variety of agricultural and livestock activities were conducted, and today, the MBP constitutes approximately 20% of farm income. The MBP is always managed in an extensive fashion with low-level breeding and feeding conditions (between 10 and 25 pigs/ha) (Gonzalez et al., 2013). The traditional feeding regime was primarily pasture, cereals (barley), and legume seeds, and the secondary food sources were mainly figs, almonds, or carob seeds from traditional rainfed tree polyculture, and several Mediterranean shrubs typical to MBP plots (Gonzalez et al., 2013; Tibau et al., 2019).

The disappearance of the biocultural landscape is closely linked to the decline in MBP numbers over the last 150 years. In addition, the effect of diseases and the more recent introduction of leaner pig breeds are the basis for the breed's dramatic status in the beginning of twenty-first century (Tibau et al., 2019). A group of MBP stockbreeders and meat processors favoured the recovery of the breed in the 1980s (Gonzalez et al., 2013). The latest census of the MBP (August, 2016) (FAO, 2017) registered 59 farms with less than 1000 breeding sows and 54 males.

The main meat product obtained from the MBP is the 'sobrassada de Porc Negre Mallorquí,' a specialty fat-rich cured sausage that has been PGI certified since 1994. The reduction in generational relay and the low financial performance of these farms call for the development of new products that can push the demand and added value of the products to create new niche markets that can improve revenues for producers. Accordingly, new products such as carpaccio (Gonzalez et al., 2013) or pork burgers (Kallas et al., 2019) have been tested that may better align with consumer demand for reduced-fat pork products.

3 Material and methods

3.1 Survey design (attributes and levels) and data collection

Following Jeanloz et al. (2016), an initial list of relevant attributes was devised through an extensive literature review, followed by an in-depth discussion and exchange with researchers on socioecological transitions in Mallorca and MBP farming. An initial pool of attributes and levels, and their graphical representation, was tested in two world café sessions[1] held with island dwellers that corresponded to urban and rural profiles,

[1] A world café is a structured conversational process intended to facilitate open and comfortable discussion and link ideas within a larger group to access the collective intelligence in the room. Participants move between a series of tables where they engage in discussion in response to a set of questions, which are predetermined for each table and focus on the specific goals of each world café. In our case each table gathered several attribute groups according to main relevant dimensions (breed related management, product dimension, and biodiversity-related issues). A café ambience is created to facilitate conversation.

respectively. A final list of attributes was selected for the construction of choice scenarios. A group valuation session was held with 15 scholars to fine-tune the questionnaire and its visual aids, followed by pilot testing with 20 people to gather parameter priors (see below).

Similar to the literature on traditional breeds, the future existence of the breed was one of the attributes considered (Zander et al., 2013). A discussion held with geneticists on the project allowed for the identification of three population threshold levels for breed survival: less than 200 sows presents a high level of risk of breed extinction, between 200 and 1000 sows presents a medium level of risk, and greater than 1000 sows presents a low level of risk.

The management attribute considered whether animals are bred outdoors, indoors, or both (50% indoors, 50% outdoors). Outdoor management allows the animals to develop their natural behaviour while improving the organoleptic features of the meat such as intramuscular fat (Tibau et al., 2019). Indoor–outdoor management is undertaken for sows and suckling piglets. Because intensification, that is, indoor breeding with external feeding inputs, is one of the strategies followed by extensive systems to improve financial performance, we included indoor breeding to seize respondents' preferences for this option.

The socioecological transition in Mallorca that reduced the presence of MBPs also entailed a loss of tree polycultures and landscape functional structure (Marull et al., 2015b). Because multifunctionality in many traditional land use systems is highest when maintained simultaneously at various levels (field, farm, and landscape) (Vos and Klijn 2000), two attributes conveyed diversity dimensions of the MBP agroecosystem at various levels. Respondents were first briefed through the provision of a location map of MBP farms in the central and southern parts of the island. The tree diversity attribute considered the diversity of domestic tree species in this area (tree polycultures), namely, the almond, fig, and carob trees that have traditionally been a food source for MBPs; due to the failure to replace of dead almond, carob and fig trees, the density and diversity of polycultures have decreased (Marull et al., 2015), with almond trees predominating if anything due to linked subsidies to this species.

The following explanation was provided to the respondents, 'in the traditional farming system in that area, each farmer would traditionally combine three different tree species in his property'. However, this is becoming less common, and we observe areas where most of the plots have two or even just one tree species (medium and low tree variety, respectively). The landscape attribute considered heterogeneity–homogeneity levels conveyed as landscape 'variety' to the respondents. Explanations and real pictures of the central part of the island were provided to respondents to illustrate the three levels. Explanations were provided to convey the low level of variety, for example, *the low-variety landscapes are characterised by monocultures where most of the land plots cultivate cereals, there are few or no tree crops, and traditional stone walls are missing*. This level was linked to the predominant trend towards more uniform land covers, tending towards the vanishing of the farmers' landscape mosaics created and maintained by traditional farming (Marull et al., 2015).

The product variety attribute considered the provisioning dimension of the MBP. Although other studies have considered the quality of food-related products (Zander et al., 2013), we followed an approach similar to that of Bernués et al. (2014), who consider the availability of products linked to the territory. By contrast, we introduced an innovative dimension in traditional food products related to this breed by considering one of the five main dimensions that characterise food innovation (Guerrero et al., 2009), to evaluate the social preferences for one of the strategies linked to traditional extensive products followed in some regions, such as developing new products that may fit better with current consumer demands (Kühne, 2010) while capturing cultural and heritage values linked to traditional breeds' products (Balogh et al., 2016; Gandini y Villa, 2003). This is particularly relevant in the case of MBPs because the main food product obtained from its meat is *sobrassada*, a spreadable cured sausage with limited market opportunities. MBP meat holds outstanding organoleptic features, and studies have shown high consumer acceptance of other meat preparations such as hamburgers (Kallas et al., 2019).

Finally, the monetary attribute considered six levels from €10 to €60. The payment vehicle was expressed as the annual household tax payment for three years. We purposefully reduced the taxation period to three years because credibility is crucial for stated preference valuation studies (Carson and Grooves, 2007) and an infinite payment vehicle would appear improbable and may thus reduce the incentive compatibility of the payment vehicle.

Table 1. Description of attributes and levels[2]

ATTRIBUTE	VARIABLE NAME	DESCRIPTION
BREED EXISTENCE	H_RISK* M_RISK L_RISK	HIGH risk of extinction (< 200 sows) MEDIUM risk of extinction (200–1000 sows) LOW risk of extinction (1000–2000 sows)
TYPE OF MANAGEMENT	OUTDOOR* OUT-IN DOOR INDOOR	Most of the time outdoors 50% outdoors, 50% indoors Most of the time indoors
TREE CROPS	1 TSP* 2 TSP 3 TSP	1 tree species, low variety 2 tree species, medium variety 3 tree species, high variety
TYPE OF LANDSCAPE	LOW* MEDIUM HIGH	Low heterogeneity Medium heterogeneity High heterogeneity
PRODUCT VARIETY	LOW* MEDIUM HIGH	Low product variety Medium product variety High product variety
COST (€/household)	0, 10, 20, 30, 40, 50, 60	

Each of the choice sets presented to the respondents depicted a future doing-nothing situation plus two alternative scenarios of change that would entail a cost for the respondent household. A D-efficient experimental Bayesian design with 24 alternatives distributed in four blocks was optimised by employing Ngene (choice Metrics 2012) for D-efficiency, retrieving a D-error of 0.0064. The design considered the priors obtained in a pilot survey conducted with 20 respondents.

The valuation questionnaire designed to implement the DCE comprised questions on knowledge of the MBP system, perception of the status quo (SQ) levels of the selected attributes, and fundraising options for a hypothetical programme to support the MBP through price increases in products and an earmarked tax increase.

To attempt to reduce the incidence of protest responses against the payment vehicle, we included a question prior to the choice cards so that the respondents expressed their preferred institution to manage taxpayers' money. Next, the respondents were asked to make their selections while considering that this institution would manage their contributions towards the most preferred scenario. Furthermore, a short, cheap-talk script was included to reduce hypothetical bias (Ladenburg et al., 2007; Varela et al., 2014c).

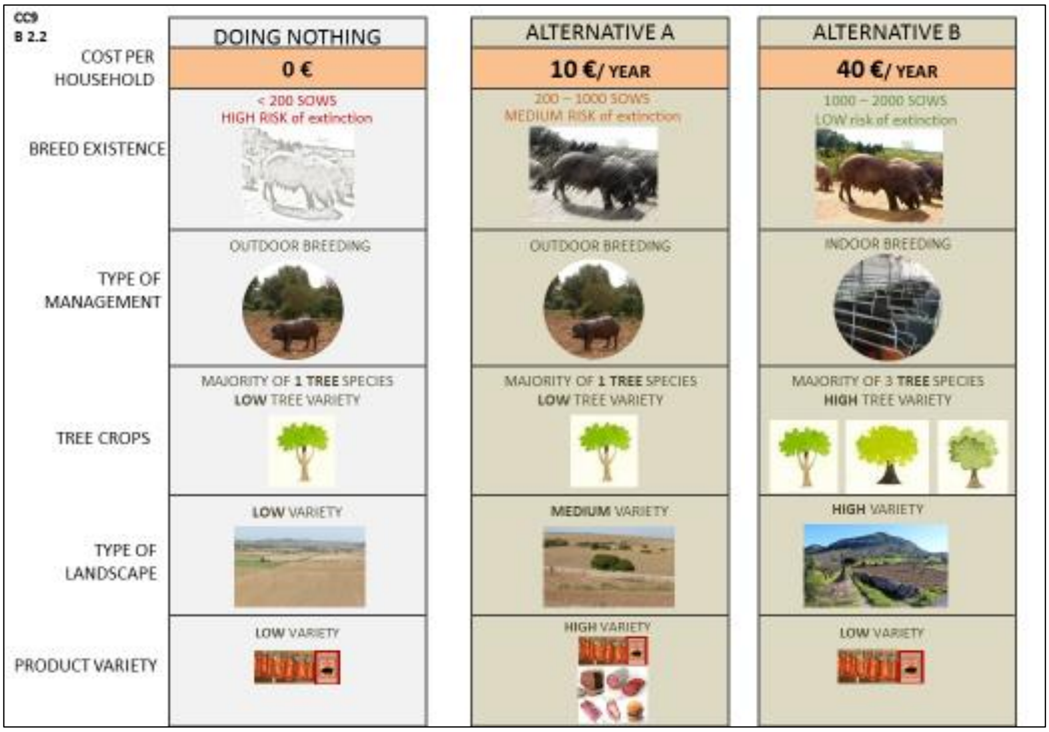
Because no established theoretical criteria or protocols have identified protest responses (Boyle and Bergstrom, 1999), we followed the usual method, where these respondents chose the SQ from either in five or six choice cards, on which the respondents were

[2] Appendix 1 shows the full list of images used to convey the attributes' levels to the participants

debriefed through a close-ended question to disentangle protesters from zero bidders (Meyerhoff et al., 2014a, 2014b).

The studies on societal preferences for rural landscapes have conducted their surveys with contrasted samples of a local–rural population and urban dwellers (i.e. living closely to the rural landscapes vs living distant from the resources) and demonstrated differences in preferences among these groups (Bernués et al., 2014; Hynes y Campbell, 2011). Our sampling strategy attached equal weights to rural (< 20,000 inhabitants) and urban (> 20,000 inhabitants) populations. Each subsample was stratified according to population size, gender, and three age groups.

Figure 1. Example of choice cards shown to respondents



3.2 Econometric approach

Latent class (LC) models (Kamakura et al., 1989) assume that the overall preference distribution comprises a combination of unobservable latent groups or classes that differ in their utility between the groups but are similar within. Finite mixing models offer the advantage of ease of interpretation and are useful for decision making and communication (Boxall y Adamowicz, 2002; Farizo et al., 2014; Provencher y Bishop, 2004; Scarpa y Thiene, 2005), whereas some practitioners favour LC approaches over continuous specifications because of superior model fit (Bujosa et al., 2010; Soliño andFarizo, 2014; William y David, 2013; Yoo y Ready, 2014). LC models impose more structure on the choice model but in exchange offer a more detailed description of segment heterogeneity in the data by using two sub-models: one for class allocation and one for within-class choice (Hess et al., 2007). Simulation procedures estimate class-specific part-worth utilities for each attribute level and assign each person a probability of belonging to each of the prespecified classes. The initial caveat of an LC that imposes homogeneity in preferences within groups is overcome by allowing random parameters within each class, which allows for another layer of preference heterogeneity within a class (Greene y Hensher, 2013). Combining LC models with random effects was initially proposed by Böckenholt (2001), and many researchers have followed this method (e.g. Bujosa et al., 2010; Justes et al., 2014; Soliño and Farizo, 2014; Varela et al., 2014).

The observed behaviour of the recurrent choice of SQ in valuation studies was probably first addressed by Samuelson and Zeckhauser (1988) and Kahnemann et al. (1991). although respondents may choose the SQ for different reasons, repeated choice of the SQ across a valuation survey typically hides some type of protest attitude (Adamowicz et al., 1998; Meyerhoff et al., 2014b, 2009; Thiene et al., 2012) where respondents reject (protest against) an aspect of the constructed market scenario (Meyerhoff et al., 2014). Studies such as these, for example, Scarpa et al. (2005), Boxall et al. (2009), Meyerhoff et al., (2014) or Meyerhoff and Liebe (2009), have delved deeper into the variables that may be related to protest responses. Despite the common procedure of deleting protest zero responses from the sample (Morrison et al. 2000), censoring them is unjustified (Jorgensen y Syme, 2000) and can lead to sample selection bias (Meyerhoff et al., 2014a).

Among the reasons explored for protesting, task complexity is suggested as one of the possible causes (Boxall et al., 2009; Thiene et al., 2012). Task complexity is closely related to higher levels of uncertainty in the responses, leading to a higher variance of parameter estimates for some respondents. Therefore, the common assumption based on equality of scale may be easily violated because respondents may display different levels of certainty when making choices, even when preferences are homogenous (Lutzeyer et al., 2018), and ignoring this may potentially imply biased estimates (Louviere and Eagle, 2006).

Until recently, LC models allowed preferences to differ from class to class, but the error variances were identical over classes (Burke et al., 2015). Modelling scale (i.e. discrimination capacity) through scale adjusted latent class (SALC) modelling was first proposed by Swait (Swait, 1994). The approach introduced by Magidson and Vermunt

(2007) was based on an LC model that controls for differences in the error variances across respondents by using discrete mixing distributions for scale and preference that allow accounting for some respondents being more consistent than others in their choices (i.e. existing different scale groups).

SALC models assume that each latent preference class may comprise subgroups of individuals that although within the same class, despite sharing the same preference structure, may display different levels of uncertainty, thereby belonging to different scale classes. In this model, respondents are probabilistically allocated to both preference and scale classes: latent segments that differ in their preference part-worth utilities, and latent subgroups that differ in their scale parameter. Scale classes (sclasses) are generally assumed to be independent of the classes, that is, the size of the sclasses is the same across latent segments. However, this assumption can be relaxed, allowing some segments to have a higher (lower) percentage of respondents belonging to a scale factor (Magidson and Vermunt, 2007).

In our study, we extended the traditional LC approach of Burton and Rigby (2009) and deterministically allocated protesters into a single class to avoid explicit consideration of these non-participants, which may have confounded the underpinning structure of other preference classes and prevented real segregation into groups (Thiene et al., 2012). We tested discrete mixture distribution (random parameter LC) approaches where protesters are identified and deterministically allocated to one class. Furthermore, we explored whether protest responses were linked to significantly different scale patterns by considering whether scale is correlated to preference class.

We departed from the conditional logit model for the response probabilities (Vermunt y Magidson, 2005):

$$P(y_{it} = m|z_{it}^{att}) = \frac{\exp(\eta_{m|z_{it}})}{\sum_{m'=1}^{M} \exp(\eta_{m'|z_{it}})} \qquad (1)$$

Where $\eta_{m|z_{it}}$ is the systematic component in the utility of alternative m for individual i and choice set t; hence, z^{att} represents attribute levels.

The term $\eta_{m|z_{it}}$ is a linear function of an alternative-specific constant β_m^{con} and attribute effects β_p^{att} (Mc Fadden, 1974), that is,

$$\eta_{m|z_{it}} = \beta_m^{con} + \sum_{p=1}^{P} \beta_p^{att} z_{itmp}^{att} \qquad (2)$$

In an LC variant of the conditional logit model, we assume that individuals are probabilistically allocated to different LCs that differ with respect to the β parameters. Thereby, the choice probabilities depend on class membership (x), and the logit model is in the following form:

$$P(y_{it} = m|x, z_{it}^{att}) = \frac{\exp(\eta_{m|x,z_{it}})}{\sum_{m'=1}^{M} \exp(\eta_{m'|x,z_{it}})} \quad (3)$$

Where $\eta_{m|x,z_{it}}$ is the systematic component in the utility of alternative m at choice set t because individual i belongs to LC x. The linear model for $\eta_{m|x,z_{it}}$ is

$$\eta_{m|x,z_{it}} = \beta_{xm}^{con} + \sum_{p=1}^{P} \beta_{xp}^{att} z_{itmp}^{att} \quad (4)$$

Thereby, the logit regression coefficients are allowed to be class specific. The probability density associated with the responses of individual i has the following form:

$$P(y_i|z_i) = \sum_{x=1}^{K} P(x) \prod_{t=1}^{Ti} P(y_{it}|x, z_{it}^{att}) \quad (5)$$

Where P(x) is the unconditional probability of belonging to class x or, equivalently, the size of LC x. The T_i repeated choices of individual i are assumed to be independent of each other on the basis of class membership.

We combine the LC with random effects continuous factors to specify the random-coefficients' conditional logit models. Continuous factor (CF) models have been proposed as an alternative to hierarchical Bayes (HB) approaches to allow for random effects, providing a more parsimonious alternative to HB estimations (Magidson et al., 2005). The CF approach superimposes a factor analytic structure on the variance–covariance matrix, assuming the coefficients follow multivariate normal distributions. Let denote the full vector of random factor scores by F_i and F_{di} denote the score of individual i on random effect number d. When these are included in a model, the structure for $P(y_i|z_i)$ becomes

$$P(y_i|z_i) = \sum_{x=1}^{K} \int_{Fi} f(F_i) P(x|z_i) P(y_i|x, z_i, F_i) dF_i \quad (6)$$

Where

$$P(y_i|x, z_{i,}F_i) = \prod_{t=1}^{Ti} P(y_{it}|x, z_{it}^{att}, z_{it}^{pre}, F_i) \quad (7)$$

The F_{di} are assumed to be standard normally distributed and mutually independent and appear in the model for the choices but not in the model for the LCs. Hence, the linear predictor in the model for the choices is expanded with the following additional term where random effects are defined for the alternative-specific constant and attributes (except cost), respectively:

$$\sum_{d=1}^{D} \alpha_{xmd}^{com} \cdot F_{di} + \sum_{d=1}^{D} \sum_{p=1}^{P} \alpha_{xpd}^{att} \cdot F_{di} \cdot z_{mitp}^{att} \qquad (8)$$

Where x stands for class membership, m for alternative, and i for individual. A critical difference with the more standard specification of random effects is that here, each F_{di} can serve as a random effect for each of the model effects, which yields parsimonious random-effects covariance structures (Magidson and Vermunt, 2004).

Because class memberships are latent, we assume the probability that person i belongs to a latent preference class x is determined according to the expression:

$$Pr_{ix} = \frac{\exp(\theta_{x0} + \theta'_x Z_i)}{\sum_{k=1}^{X} \exp(\theta_{k0} + \theta'_k Z_n)}, \quad x = 1, \dots, X \qquad (9)$$

where θ_{q0} is a scalar, Z_n is an R-dimensional vector of individual covariates, and $\theta_q = (\theta_{q1}, \dots, \theta_{qR})$ is a vector of coefficients compatible with Z_n.

For scale-extended models, we followed Thiene et al. (2015), Lutzeyer et al. (2018), and Vermunt (2008) and refer to the interested reader to these publications for the sake of brevity. Within each x preference class and s scale class, the choice probability for alternative m in choice set t is a conditional logit:

$$Pr_{imt|x,s} = \frac{\exp(\lambda_s \beta'_x X_{imt})}{\sum_{k=1}^{M} \exp(\lambda_s \beta'_x X_{ikt})}, \quad s = 2, \dots, S \qquad (10)$$

where β_x is a vector of utility function parameters; X_{imt} is a vector that includes characteristics of the choice alternative, often interacted with characteristics of the individual; λ_s is the scale parameter; and M the number of choice alternatives. Heterogeneity in preferences is given by the discrete range of values that β_x and λ_s can take, where λ_s is the scale parameter associated with the type I extreme value distributed random variable error term.

Respondents in each s scale class have on average the same degree of determinism in their choices or the same ability to discriminate their preference using the arguments in the indirect utility function. Similarly, for each preference class x, all respondents in that class like all the MBP-related attributes with the same relative taste intensity. We also include a shared component δ_{xs} across the scale-preference class to account for potential correlation across membership probabilities of scale and classes, that is, we allow for the following: a higher scale might be positively correlated with preference classes where selected attributes have utility weights, or vice-versa. To this end, we assume that the multinomial logit membership probabilities that person i belongs to x preference class and s scale class are semi-parametric multinomial logit:

$$\Pr(i \in x, s) = \frac{\exp(\theta_s + \omega_x + \delta_{x,s})}{\sum_c \sum_s \exp(\theta_s + \omega_x + \delta_{x,s})} \qquad (11)$$

where each class has a constant for the scale value θ_s and one for the scale value ω_x. As Thiene et al. (2015) noted, in correlated scale and preference classes, an easy check is that joint membership probability for scale-preference class c, s is not the product of the marginal probabilities for membership to scale class and preference class whenever $\delta_{xs} \neq 0$.

4 Results

4.1 Survey details

A sample of 400 respondents with 211 and 189 respondents for rural and urban areas, respectively, were surveyed in April 2017 through face-to-face questionnaires. The sample shows representativeness with respect to the total population in terms of gender and age distribution for rural and urban areas (Table 1).

Table 2. Percentage of gender and age representativeness of the sample

	SAMPLE	POPULATION	Chi- square
GENDER			
URBAN			
Male	49.73	48.44	P(χ^2 >0.125) =0.724
Female	50.27	51.56	
RURAL			
Male	46.44	52.2	P(χ^2 >1.19) =0.275
Female	53.56	49.8	
AGE CLASSES			
URBAN			
20–39	40.10	36.59	P(χ^2 >0.983) =0.612
40–64	41.71	44.05	
>65	18.18	19.36	
RURAL			
20–39	23.83	29.25	P(χ^2 >3.443) =0.179
40–64	45.79	44.3	
>65	30.37	26.44	

We identified 144 respondents as protesters, which is 36% of the total. Protesters were serial selectors of the SQ option who also chose one of these two options in the debriefing question: ‘I already pay enough taxes, and the government should use that money to fund this type of initiative’ or ‘I would collaborate if the method of raising funds was different’. Zero bidders (i.e. genuine zeros) were those who chose one of the following two options: ‘I do not think any of the proposed measures would have any positive effect’ or ‘Other measures should be implemented to protect the breed’.

Chi-square tests were conducted to test for differences between urban and rural subsamples and between protesters and non-protesters: 45% of the rural subsample showed protesting behaviour, and protesters in the urban subsample accounted for 25.7%. Unemployment is significantly higher among urban (9%) compared with rural respondents (6%). Retired people in rural areas peaked at 27% and was 16.6% in urban areas. Most of the low-income group respondents belonged to rural areas (68%).

4.2 Econometric models: preferences and willingness to pay (WTP)

The number of protesters in the sample is high but similar to that attained in other studies (e.g. Hoyos et al., 2012; Valasiuk et al., 2017; Varela et al., 2014a). Removing these observations from econometric estimations can lead to sample selection bias and WTP estimates that are not comparable across surveys (Meyerhoff et al., 2014b).

Therefore, we applied a finite mixing approach to manage preference heterogeneity (Burton and Rigby, 2009) while also testing the impact of deterministically allocating protest responses to one class by following Thiene et al. (2012). We tested the impact of deterministic protest response allocation in LC and random parameter LC models. We assume that attributes behave randomly in two ways: a continuous random factor effect for all the classes and a specific random factor component for each class. This specification improves the accuracy of the model since allows isolating the common and specific random factor components. Furthermore, uncertainty in the respondents would be reflected in scale differences and not only preference differences across respondents. SALC models were estimated both for uncorrelated and correlated scale and preference class sizes and for both deterministic and non-deterministic allocation of protesters to one class. Table 3 shows the information criteria and class sizes for the different families of models estimated.

LC models considering fixed parameter effects and random parameter effects were estimated ranging from two to six classes. These models were also estimated for deterministic protester allocation. To select our best models between those specifications tested, we used model fit along with model plausibility, the significance of the parameters' estimates and external validity (Hynes et al., 2008; Scarpa y Thiene, 2011). The optimal number of classes was determined in an iterative procedure by comparing models on the basis of Bayesian information criterion (BIC), Akaike information criterion (AIC) and Akaike information criterion 3 (AIC3). The latter, according to Andrews and Currim (2003) is the best-performing criterion when determining the optimal number of classes in logit models, supported by the AIC and BIC. All the models adopt effects coding for all non-monetary parameters. Therefore, the magnitude of the base case level coefficient is assumed to be equal to the negative sum of the utility weights for the other estimated categories (Louviere et al., 2000; Lusk et al., 2003)[3].

Information on these model fitting and scale estimates are found in Table 3.

In both the fixed and random parameter latent class models with free allocation of respondents, the 3-class models provide the best balance between information criteria and plausibility and this also stands for their protester-allocated versions. Based on these outcomes, the scale-adjusted (SALC) models are estimated for 3-class structure to allow for comparability. Among these, the SALC models where correlation is allowed between preference and scale classes provide better performance and hence are selected for reporting (see tables 6 and 7).

The models with deterministic protester allocation to one class provide lower performance than their free-allocation counterparts. As noted by Thiene et al. (2012), imposing this type of constraints has significant implications on model performance.

The outcome of the random parameter latent class model with free protester allocation is reported in table 4. In this model roughly half of the respondents are allocated to class 1, while class 2 accounts for 27% of the respondents and the remainder 22% are found in class 3.

The respondents in class 1 show a general preference for the status quo as indicated by the sign and significance of the ASC. They reject scenarios of low and medium risk for the breed and support the current high risk of extinction level. Also, they support

[3] Following Domínguez-Torreiro and Soliño (2011) and Varela et al. (2014), an additional column representing the adjusted marginal utility gains from the base level situation for each of the levels of the effects coded attributes has been included in Tables 4, 5, and 6 to increase the clarity of the interpretation of the results.

management changes towards intensification (indoor breeding) and low diversity of tree species. The price attribute is significant and with the expected sign.

In contrast, the respondents in class 2 reject the status quo scenario proposed, else things equal, and prefer low risk extinction scenarios for the breed, being this attribute level together with the rejection of indoor breeding, the two attributes that most importantly shape their preferences, followed by a rejection of increased tree species diversity. The monetary attribute is significant and negative as expected.

Respondents in class 3 show a general preference for the status quo scenario as indicated by the ASC. The current base levels of high risk of extinction for the breed, outdoor management and low diversity of tree crops contribute to increase their utility. Positive and significant preferences are shown for improving landscape heterogeneity and product variety to high and medium levels, respectively. However, the price attribute shows a positive and significant sign, indicating that these respondents are not trading on the attributes based on their budget restrictions and may be showing yea saying patterns.

The overall preference picture in this model shows support for the status quo situation for most attributes. Improving the conservation level for the breed is only supported by 26% of the sample while intensification management patterns are supported by half of the sampled population while low tree diversity is generally favoured. Improvement measures such as increasing landscape and product variety are supported by less than one fourth of the sampled respondents but their response pattern seems to reveal moral concerns rather than trading on budget restrictions. The results of the model show significant cost parameters for all the preference classes while in contrast, one third of the sample was identified as protest responses and accordingly non-significant estimates would be expected for them. Therefore, we hypothesize that the share of protesters may confound the underpinning structure of other preference classes and prevent the real segregation into groups (Thiene et al., 2012).

Results for the deterministic protester allocation counterpart model are reported in table 5.

Class 1, gathers the protest responses that amount 35% of the sample. All the attributes retrieve non-significant values, in accordance with the protesting behaviour of the respondents allocated to it. Respondents in this class show, as expected, no significant parameter estimates and a preference for the status quo situation as indicated by the sign and significance of the ASC.

Class 2 accounts for 41% of the sample. ASC estimates indicate that ceteris paribus, respondents in this group prefer alternative scenarios to the status quo. Improving the conservation status for the breed does not shape the preferences of respondents in this group, similarly to diversity at the (tree) species and landscape level. Combined indoor and outdoor management is supported by this group, and indoors breeding is rejected. Regarding product variety, respondents in this group significantly support high-variety options for MBP products and reject the low variety current situation. The cost attribute retrieves significant estimates and with the expected sign.

Class 3 accounts for 24% of respondents that show a significant positive willingness to select alternative scenarios, rejecting the SQ scenario. Regarding breed survival, respondents significantly support the low risk extinction option. They also demonstrate support for traditional outdoor management and reject mixed indoor-outdoor and indoor options. The high tree diversity level contributes to positively shape their preferences while landscape and product diversity retrieve non-significant estimates. Finally, the cost attribute is negative and significant.

The free and deterministic allocated SALC models are shown in Tables 6 and 7. In both models the sclass2 accounts for the lower scale estimates (and hence higher estimate variance).

The free allocated SALC model accounts for more than half of the sample in preference class 1. Utility of individuals in this class is only shaped by the ASC, retrieves negative and significant estimates for non-status quo scenarios. Class 2 accounts for 12% of the respondents. Utility of respondents in this group is ceteris paribus reduced by the status quo scenario. The high risk extinction level reduced the utility of respondents while they show positive and significant estimates for medium and low risk extinction levels. The management attribute also contributes to shape the preferences of respondents in this group, with positive estimates for combined outdoor-indoor management. Increasing tree diversity up to three species and product availability to medium level also contribute to increase their utility. Finally, this is the only class showing significant estimates for the cost attribute. Class 3 in this model accounts for roughly one third of the sample that would favour alternative scenarios to the status quo for breed and tree diversity. The scale structure of this model reveals that 40% of the sample belongs to sclass2, holding a lower scale parameter and hence higher estimate variance than respondents in sclass1. Most of these respondents (28% of the total sample) are found in preference class 2.

The SALC model with deterministic allocation of protesters to preference class 1, distributes 28% of respondents to class 2 and the remainder 37% in class 3. Respondents in class 2 reject alternative scenarios to the status quo. Only outdoor management significantly determines their preferences together with the cost of the proposed alternatives. Class 3 shows a broader range of attributes defining respondents' preferences and an overall preference for scenarios alternative to the status quo. Low risk extinction level and improved tree and landscape diversity increase their utility. The sample is distributed approximately in halves between sclass1 and 2. Respondents in sclass2 are mostly found in preference class 3, the one with a wider range of attributes determining their preferences.

Following the recommendation by Davis et al. (2019), we also report in Appendix 2 the results of the SALC correlated models renormalised so that sclass2 takes the value of 1 for its scale parameters.

Table 3. Information criteria values of the estimated models

	MODEL	LL	BIC	AIC	AIC3	NPar	R2	CLASS SIZES
1	CL	-2275,1042	4628,0975	4576,2084	4589,2084	13	0.0245	
2	RPL	-1243,8189	2643,4158	2539,6377	2565,6377	26	0.6376	
LATENT CLASS MODELS (fixed effects)								
3	2CLASS	-1289,3235	2740,4165	2632,6469	2659,6469	27	0.5682	0,5412 0,4588
4	3CLASS	-1213,7015	2673,0530	2509,4030	2550,4030	41	0.6256	0,5268 0,3075 0,1657
5	4CLASS	-1180,1984	2689,9273	2470,3967	2525,3967	55	0,6620	0,5266 0,2939 0,1017 0,0778
6	5CLASS	-1152,3080	2718,0271	2442,6160	2511,6160	69	0,7035	0,5265 0,2190 0,0996 0,0805 0,0745
7	6CLASS	-1128,8133	2754,9181	2423,6265	2506,6265	83	0,7327	0,5263 0,1765 0,1334 0,0782 0,0459 0,0397
ALLOCATED LATENT CLASS MODELS (fixed effects)								
8	2CLASS	-1937,0023	4035,7741	3928,0046	3955,0046	27	0,2780	0,3554 0,6446
9	3CLASS	-1446,5309	3138,7119	2975,0618	3016,0618	41	0,5643	0,3549 0,4455 0,1995
10	4CLASS	-1446,7750	32A23,0806	3003,5501	3058,5501	55	0,5643	0,3547 0,4453 0,1993 0,0006
11	5CLASS	-1446,9223	3307,2556	3031,8445	3100,8445	69	0,5643	0,3546 0,4452 0,1992 0,0005 0,0005
12	6CLASS	-1447,0208	3391,3331	3060,0415	3143,0415	83	0,5643	0,3545 0,4451 0,1991 0,0004 0,0004 0,0004
RANDOM EFFECTS LATENT CLASS MODELS								
13	2CLASS	-1144,6667	2666,7956	2415,3334	2478,3334	63	0.7804	0,7900 0,2100
14	3CLASS	-1104,4930	2742,2264	2386,9860	2475,9860	89	0.8376	0,5131 0,2689 0,2180
15	4CLASS	-1067,9087	2824,8358	2365,8174	2480,8174	115	0.9017	0,4236 0,3453 0,1241 0,1071
16	5CLASS	-1031,0742	2906,9449	2344,1484	2485,1484	141	0.9319	0,3750 0,1828 0,1791 0,1509 0,1122
17	6CLASS	-1025,8659	3052,3064	2385,7318	2552,7318	167	0.9187	0,5454 0,1404 0,1093 0,0810 0,0626 0,0613
ALLOCATED RANDOM EFFECTS LATENT CLASS MODELS								
18	2CLASS	-1333,2585	3043,9793	2792,5170	2855,5170	63	0,7107	0,3554 0,6446
19	3CLASS	-1276,6573	3086,5550	2731,3147	2820,3147	89	0,8057	0,3549 0,4083 0,2367
20	4CLASS	-1237,7119	3164,4422	2705,4237	2820,4237	115	0,8486	0,3547 0,4157 0,1317 0,0979
21	5CLASS	-1203,5655	3251,9274	2689,1309	2830,1309	141	0,8813	0,3546 0,2778 0,1923 0,0906 0,0846
22	6CLASS	-1178,6313	3357,8372	2691,2626	2858,2626	167	0,9170	0,3545 0,2158 0,1964 0,0996 0,0768 0,0569

SALC UNCORRELATED class and sclass								
23	3CLASS Sclass1=0	-1191,8239	2641,2807	2469,6477	2512,6477	43	0.6595	sclass Class 1 2 1 2 3 0,8958 0,1042 0,5707 0,3577 0,0716
SALC CORRELATED class and sclass								
24	3class Sclass1=0 Sclass2=-2.6202	-1188,7543	2641,1331	2465,5086	2509,5086	44	0.6837	sclass Class 1 2 1 2 3 0,5991 0,4009 0,5624 0,1197 0,3179 sclass 1 1 1 2 2 2 Class 1 2 3 1 2 3 0,5161 0,0509 0,0344 0,0464 0,0688 0,2835
ALLOCATED SALC UNCORRELATED class and sclass*								
25	3CLASS	-1390,3691	3038,3711	2866,7381	2909,7381	43	0,6083	sclass1 sclass2 class1 class2 class3 0,8985 0,1015 0,3549 0,2763 0,3687
ALLOCATED SALC CORRELATED class and sclass								
26	3CLASS Sclass1=0 Sclass2=-2,8026	-1385,0366	3033,6977	2858,0733	2902,0733	44	0,6022	sclass1 sclass2 class1 class2 class3 0,5249 0,4751 0,3549 0,2763 0,3687 sclass 1 1 1 2 2 2 Class 1 2 3 1 2 3 0,3515 0,1712 0,0022 0,0035 0,1051 0,3665

Table 4. Random parameter latent 3-class model with free allocation of protesters

		Class 1			Class 2			Class 3			Wald	p value
Class Size		0.5131			0.2689			0.2180				
		Parameters	z value	Adj[a]	Parameters	z value	Adj[a]	Parameters	z value	Adj[a]		
ASC	Status Quo	**4.8570**	**5.4286**		**5.0909**	**2.0945**		**3.2356**	**2.1377**		36.6277	0.000
	Alternative A	**-1.9295**	**-4.2287**	**-6.7865**	**-3.0659**	**-2.2115**	**-8.1568**	-0.9361	-1.0399	-4.1717		
	Alternative B	**-2.9274**	**-5.8949**	**-7.7844**	-2.0250	-1.3709	-7.1159	**-2.2995**	**-3.0373**	**-5.5351**		
EXIST	H_RISK*	**1.6210**	**3.1319**		**-5.7802**	**-3.0553**		**6.6760**	**5.3421**		36.9396	0.000
	M_RISK	**0.7343**	**2.5617**	**-0.8867**	-1.0647	-0.9992	4.7155	**-1.1225**	**-1.7546**	**-7.7985**		
	L_RISK	**-2.3553**	**-4.2295**	**-3.9763**	**6.8449**	**3.1029**	**12.6251**	**-5.5535**	**-5.5562**	**-12.2295**		
MNG	OUTDOOR*	0.5025	-1.2350		**6.6979**	**4.0542**		**1.3014**	**1.5929**		37.4360	0.000
	OUT-IN DOOR	**-1.2838**	**-1.7306**	**-1.7863**	-0.2010	-0.0846	-6.8989	1.1159	1.0585	-0.1855		
	INDOOR	**1.7863**	**3.2319**	**1.2838**	**-6.4969**	**-2.6804**	**-13.1948**	**-2.4173**	**-3.0594**	**-3.7187**		
TSP	1*	**1.2002**	**1.7684**		**6.6034**	**2.1725**		**2.5769**	**2.0378**		20.0091	0.003
	2	-0.8846	-1.4847	-2.0848	**-4.4439**	**-2.6589**	**-11.0473**	**-5.4037**	**-3.6422**	**-7.9806**		
	3	-0.3156	-0.6371	-1.5158	-2.1596	-0.6969	-8.763	**2.8267**	**2.8504**	**0.2498**		
LAND	LOW*	-0.0188	-0.0373		0.8388	0.4667		-1.4553	-1.3378		14.9468	0.021
	MEDIUM	-0.4419	-1.0849	-0.4231	-3.1001	-1.2521	-3.9389	**-1.6230**	**-2.2792**	**-0.1677**		
	HIGH	0.4607	0.8280	0.4795	2.2613	0.6418	1.4225	**3.0782**	**2.9500**	**4.5335**		
PROD	LOW*	0.4545	1.4158		1.0398	0.9549		**-3.1120**	**-3.5445**		18.8118	0.005
	MEDIUM	-0.3130	-0.6892	-0.7675	-1.5719	-1.2963	-2.6117	**2.0978**	**1.7084**	**5.2098**		
	HIGH	-0.1415	-0.3668	-0.596	0.5321	0.4565	-0.5077	1.0143	1.1072	4.1263		
PRICE		**-0.0264**	**-3.2117**		**-0.3080**	**-4.7607**		**0.0634**	**2.1573**		33.6257	0.000
Continuous random Factor 1 (SDPD per Class)												
ASC	Status Quo	**5.8367**	**5.0315**		**10.8536**	**4.4596**		**2.1251**	**1.8101**		32.8918	0.000
	Alternative A	**-2.7613**	**-4.7664**		**-6.6976**	**-4.3760**		-0.5896	-0.7633			
	Alternative B	**-3.0753**	**-5.1218**		**-4.1559**	**-3.3085**		**-1.5355**	**-2.8256**			
EXIST	H_RISK	-0.2276	-0.7767		**10.4301**	**5.3441**		**2.7080**	**2.9662**		32.9835	0.000
	M_RISK	0.3667	1.5990		**-7.5119**	**-4.9229**		**1.2114**	**2.0439**			
	L_RISK	-0.1391	-0.7046		**-2.9182**	**-2.4668**		**-3.9194**	**-4.2473**			
MNG	OUTDOOR	-0.0387	-0.1560		0.5282	0.4482		**-2.9634**	**-3.8821**		30.2102	0.000
	OUT-IN DOOR	**0.7082**	**2.0365**		**8.0121**	**3.0420**		**2.5152**	**2.6337**			
	INDOOR	**-0.6695**	**-2.8516**		**-8.5404**	**-3.6743**		0.4482	0.6928			

TSP	1	**-0.6047**	**-1.7535**		1.2684	0.6309		-0.2764	-0.3392		22.7919	0.001
	2	0.1007	0.3435		**-3.7460**	**-2.4867**		**4.7388**	**4.1255**			
	3	0.5040	1.6306		2.4776	1.3233		**-4.4624**	**-4.1089**			
LAND	LOW	-0.0018	-0.0056		**-3.0919**	**-1.8637**		**-1.6355**	**-2.1376**		30.1617	0.000
	MEDIUM	**0.5371**	**2.1769**		**6.7046**	**3.7833**		**-2.4856**	**-3.4861**			
	HIGH	**-0.5354**	**-1.8382**		-3.6127	-1.6061		**4.1211**	**3.8570**			
PROD	LOW	-0.3081	-1.4135		-0.6034	-0.6473		**2.8731**	**3.6056**		24.1258	0.001
	MEDIUM	-0.0034	-0.0100		**-3.8063**	**-2.8737**		**-6.4050**	**-4.3186**			
	HIGH	0.3116	1.1551		**4.4098**	**3.4322**		**3.5319**	**3.7477**			
Continuous random Factor 2 (Common SDPD)												
ASC	Status Quo	**15.0007**	**5.8587**								41.0876	0.000
	Alternative A	**-6.4682**	**-5.1585**									
	Alternative B	**-8.5324**	**-6.2587**									
EXIST	H_RISK	**4.4632**	**4.6444**								26.0879	0.000
	M_RISK	**1.0667**	**2.2975**									
	L_RISK	**-5.5300**	**-5.1072**									
MNG	OUTDOOR	-0.4543	-0.6391								11.5025	0.0032
	OUT-IN DOOR	**-2.7519**	**-1.9560**									
	INDOOR	**3.2062**	**3.0607**									
TSP	1	**3.2930**	**2.6797**								7.3746	0.025
	2	**-1.8044**	**-1.6209**									
	3	**-1.4886**	**-1.6834**									
LAND	LOW	-0.1939	-0.2227								4.0797	0.13
	MEDIUM	**-1.3445**	**-1.8567**									
	HIGH	**1.5384**	**1.6063**									
PROD	LOW	**0.9631**	**1.7953**								3.3008	0.19
	MEDIUM	-0.5361	-0.7017									
	HIGH	-0.4271	-0.6419									

[*] Base-level situation for the effects-coded attributes.

[a] Adjusted marginal utility gains from the base-level situation for the effects-coded attributes.

Table 5. Random parameter latent 3-class model with deterministic protester allocation

		Class 1- protesters			Class 2			Class 3			Wald	p value
Class Size		0.3549			0.4083			0.2367				
		Parameters	z value	Adj[a]	Parameters	z value	Adj[a]	Parameters	z value	Adj[a]		
ASC	Status Quo	**19.0363**	**2.6698**		**-0.7699**	**-1.8842**		**-4.9580**	**-3.6240**		28.7014	0.000
	Alternative A	-5.7077	-1.1490	-24.744	**0.4058**	**1.8730**	**1.1757**	**2.1114**	**2.8637**	**7.0694**		
	Alternative B	**-13.3285**	**-3.0832**	**-32.3648**	**0.3640**	**1.5867**	**1.1339**	**2.8466**	**4.2353**	**7.8046**		
EXIST	H_RISK*	4.6591	0.9671		-0.1071	-0.4490		**-5.0138**	**-6.1905**		41.6397	0.000
	M_RISK	-1.6958	-0.2347	-6.3549	0.0600	0.3279	0.1671	-0.5435	-1.2748	4.4703		
	L_RISK	-2.9633	-0.6032	-7.6224	0.0470	0.1891	0.1541	**5.5573**	**5.8979**	**10.5711**		
MNG	OUTDOOR*	-0.4404	-0.0763		-0.0335	-0.1419		**4.2437**	**5.3543**		36.3947	0.000
	OUT-IN DOOR	1.2314	0.1580	1.6718	**0.7687**	**2.8357**	**0.8022**	**1.4584**	**1.9830**	**-2.7853**		
	INDOOR	-0.7910	-0.1653	-0.3506	**-0.7352**	**-3.2830**	**-0.7017**	**-5.7022**	**-4.9582**	**-9.9459**		
TSP	1*	5.8884	0.7180		0.1463	0.4301		-0.5971	-1.1652		17.7957	0.007
	2	-4.6912	-0.6811	-10.5796	-0.5382	-1.4786	-0.6845	-1.4391	-2.5836	-0.842		
	3	-1.1971	-0.1904	-7.0855	0.3919	1.5255	0.2456	**2.0362**	**3.4690**	**2.6333**		
LAND	LOW*	-3.7997	-0.5472		-0.0643	-0.1838		-0.4463	-0.9733		3.4050	0.76
	MEDIUM	0.7791	0.1542	4.5788	0.2564	1.1391	0.3207	0.3986	0.9719	0.8449		
	HIGH	3.0206	0.3225	6.8203	-0.1921	-0.6316	-0.1278	0.0477	0.1007	0.4940		
PROD	LOW*	-0.1191	-0.0291		**-0.4808**	**-2.2808**		0.4661	1.3217		10.1363	0.12
	MEDIUM	1.0016	0.1802	1.1207	-0.0774	-0.3475	0.4034	-0.2485	-0.6702	-0.7146		
	HIGH	-0.8825	-0.1160	-0.7634	**0.5582**	**2.7166**	**1.039**	-0.2176	-0.6092	-0.6837		
PRICE		-0.0498	-0.3882		**-0.0206**	**-2.6068**		**-0.0460**	**-2.5089**		13.7753	0.003
Continuous random Factor 1 (SDPD per Class)												
ASC	Status Quo	5.0775	1.1877		**7.8698**	**6.6481**		**5.6553**	**3.5651**		52.0443	0.000
	Alternative A	-0.5168	-0.1573		**-3.7052**	**-6.3225**		**-1.4589**	**-1.6030**			
	Alternative B	**-4.5607**	**-1.8168**		**-4.1646**	**-6.7146**		**-4.1964**	**-5.2661**			
EXIST	H_RISK	2.0534	0.6183		**0.4453**	**1.7760**		**2.8703**	**3.7281**		44.3231	0.000
	M_RISK	0.1068	0.0250		**0.3183**	**1.6206**		**3.1759**	**4.5554**			
	L_RISK	-2.1602	-0.6505		**-0.7636**	**-3.1842**		**-6.0462**	**-5.4089**			
MNG	OUTDOOR	-0.0352	-0.0117		0.0560	0.2031		-0.8670	-1.2727		23.7182	0.001
	OUT-IN DOOR	-0.9454	-0.2275		**1.1221**	**2.9792**		-1.1987	-1.1444			
	INDOOR	0.9806	0.2996		**-1.1781**	**-4.1372**		**2.0657**	**2.4470**			

TSP	1	7.4108	1.4238		-0.3758	-1.1384		0.5447	0.6067		17.4746	0.008
	2	-2.0151	-0.4945		**0.6363**	**1.7412**		**1.5896**	**2.0242**			
	3	-5.3957	-1.1091		-0.2605	-0.8194		**-2.1343**	**-3.2546**			
LAND	LOW	**-7.7913**	**-1.7565**		-0.1556	-0.4599		0.8109	0.9275		27.8487	0.000
	MEDIUM	1.3255	0.3663		**0.7720**	**2.7845**		**-3.3593**	**-4.2160**			
	HIGH	6.4658	1.0883		**-0.6164**	**-2.1214**		**2.5484**	**2.7160**			
PROD	LOW	0.5862	0.2234		**-0.7460**	**-2.9902**		0.4678	1.0902		32.3070	0.000
	MEDIUM	0.5181	0.1720		0.0529	0.1519		**2.5551**	**4.1048**			
	HIGH	-1.1043	-0.2637		**0.6931**	**2.3179**		**-3.0229**	**-4.7683**			
Continuous random Factor 2 (Common SDPD)												
ASC	Status Quo	**6.2917**	**5.8069**								33.8213	0.000
	Alternative A	**-3.1384**	**-5.6552**									
	Alternative B	**-3.1533**	**-5.7675**									
EXIST	H_RISK	0.0255	0.1052								0.0270	0.99
	M_RISK	0.0222	0.0916									
	L_RISK	-0.0477	-0.1642									
MNG	OUTDOOR	0.1856	0.7322								8.7514	0.013
	OUT-IN DOOR	**0.7648**	**2.1480**									
	INDOOR	**-0.9504**	**-2.9583**									
TSP	1	**0.7867**	**2.3647**								6.5024	0.039
	2	**-0.8182**	**-2.2793**									
	3	0.0314	0.1101									
LAND	LOW	0.1219	0.3600								0.9353	0.63
	MEDIUM	0.1300	0.5873									
	HIGH	-0.2520	-0.8540									
PROD	LOW	-0.0621	-0.2625								0.1451	0.93
	MEDIUM	0.1053	0.3772									
	HIGH	-0.0432	-0.1809									

[*] Base-level situation for the effects-coded attributes.

[a] Adjusted marginal utility gains from the base-level situation for the effects-coded attributes.

Table 6. Scale-adjusted latent class (SALC) model with free allocation of protesters that allows for correlated preference and class size

	CLASS 1	CLASS 2	CLASS 3	OVERALL

Preference Class Size		0.5624			0.1197			0.3179				
PREFERENCE CLASS MODEL PARAMETERS												
		Parameters	z value	Adj[a]	Parameters	z value	Adj[a]	Parameters	z value	Adj[a]	Wald	p-value
ASC	Status Quo*	5.4018	1.5965	5	**-2.9042**	**-1.8158**		**-34.4538**	**-3.4393**		13.285	0.010
	Alternative A	-1.1864	-0.6174	-6.5882	1.2120	1.1595	4.1162	**15.5098**	**3.3417**	**49.9636**		
	Alternative B	**-4.2155**	**-1.9278**	**-9.6173**	1.6923	1.6186	4.5965	**18.9441**	**3.4932**	**53.3979**		
EXIST	H_RISK*	2.9819	1.2094		**-6.8304**	**-2.9604**		**-6.0920**	**-2.7628**		12.163	0.016
	M_RISK	-5.1354	-1.5268	-8.1173	**2.8534**	**2.3680**	**9.6838**	-0.1635	-0.1788	5.9285		
	L_RISK	2.1534	0.6449	-0.8285	**3.9770**	**2.5162**	**10.8074**	**6.2555**	**3.2181**	**12.3475**		
MNG	OUTDOOR*	2.6494	0.7618		**-1.9770**	**-1.9027**		0.4950	0.3696		6.812	0.15
	OUT-IN DOOR	-4.0796	-0.7587	-6.729	**5.7313**	**2.6282**	**7.7083**	-1.1060	-0.6399	-1.601		
	INDOOR	1.4302	0.5674	-1.2192	**-3.7543**	**-2.6162**	**-1.7773**	0.6109	0.5006	0.1159		
TSP	1*	-0.1431	-0.0520		-0.8243	-0.6497		0.7901	0.3718		0.599	0.96
	2	-2.1610	-0.9019	-2.0179	**-2.5872**	**-1.8714**	**-1.7629**	-3.3088	-1.4899	-4.0989		
	3	2.3041	1.1815	2.4472	**3.4115**	**2.4376**	**4.2358**	**2.5188**	**1.8941**	**1.7287**		
LAND	LOW*	-1.8673	-0.6551		1.9600	1.4037		0.7302	0.4121		6.908	0.14
	MEDIUM	2.1259	1.0368	3.9932	0.7500	0.9652	-1.21	**-3.2239**	**-2.1563**	**-3.9541**		
	HIGH	-0.2586	-0.0782	1.6087	**-2.7100**	**-1.7435**	**-4.67**	2.4937	1.3672	1.7635		
PROD	LOW*	-1.5562	-0.9423		**-1.7048**	**-1.7712**		0.7458	0.7854		6.260	0.18
	MEDIUM	-1.4580	-0.9894	0.0982	**2.9095**	**1.8938**	**4.6143**	**-2.0887**	**-1.6461**	**1.3429**		
	HIGH	3.0142	1.3335	4.5704	-1.2048	-1.4146	0.5	1.3429	1.2015	0.5971		
PRICE		-0.0615	-0.3632		**-0.3568**	**-3.0784**		-0.0551	-0.7957		5.098	0.078
SCALE MODEL PARAMETERS												
sClass1 (ln λ_1)		0.0000									107.589	0.000
sClass2 (ln λ_2)		**-2.6202**	**-10.3725**									
sCLASS SIZE												
sClass1		0.5991										
sClass2		0.4009										
CLASS AND SCLASS												
Sclass		1	1	1	2	2	2					
Class		1	2	3	1	2	3					
ClassSize		0.5161	0.0509	0.0344	0.0464	0.0688	0.2835					

CLASS AND SCLASS COVARIANCES/ASSOCIATIONS					
sclass(1)<-> Class(1)	0.0000			54.0009	0.000
sclass(1)<-> Class(2)	0.0000				
sclass(1)<-> Class(3)	0.0000				
sclass(2)<-> Class(1)	**-2.4098**	**-6.9206**			
sclass(2)<-> Class(2)	0.3004	0.7898			
sclass(2)<-> Class(3)	**2.1095**	**5.4370**			

[*] Base-level situation for the effects-coded attributes.
[a] Adjusted marginal utility gains from the base-level situation for the effects-coded attributes.

Table 7. Scale-adjusted latent class (SALC) model with deterministic allocation of protesters that allows for correlated preference and class size

		CLASS 1			CLASS 2			CLASS 3			OVERALL	
Preference Class Size		0.3549			0.2763			0.3687				
PREFERENCE CLASS MODEL PARAMETERS												
		Parameters	z value	Adj[a]	Parameters	z value	Adj[a]	Parameters	z value	Adj[a]	Wald	p-value
ASC	Status Quo*	3.5314	1.1113		3.6627	1.1405		**-35.2164**	**-3.4233**		14.7477	0.022
	Alternative A	-0.0143	-0.0060	-3.5457	-0.7506	-0.3480	-4.4133	**15.4970**	**3.2725**	**50.7134**		
	Alternative B	**-3.5171**	**-1.6217**	**-7.0485**	**-2.9122**	**-1.6664**	**-6.5749**	**19.7195**	**3.5006**	**54.9359**		
EXIST	H_RISK*	2.0939	0.6031		-2.4469	-0.8274		**-9.9121**	**-3.0943**		11.2836	0.80
	M_RISK	-1.4713	-0.3895	-3.5652	0.5189	0.2692	2.9658	0.8970	0.7365	10.8091		
	L_RISK	-0.6227	-0.2108	-2.7166	1.9279	0.9870	4.3748	**9.0151**	**3.2801**	**18.9272**		
MNG	OUTDOOR*	-0.3159	-0.1015		**3.9119**	**1.6953**		0.7506	0.4461		3.4541	0.75
	OUT-IN DOOR	0.2390	0.0552	0.5549	1.1005	0.4361	-2.8114	-0.3328	-0.1393	-1.0834		
	INDOOR	0.0769	0.0267	0.3928	-5.0124	-1.5128	-8.9243	-0.4178	-0.2582	-1.1684		
TSP	1*	1.1350	0.1976		0.8985	-0.2648		1.1546	0.4750		4.6694	0.59
	2	-2.9451	-0.5811	-4.0801	0.2725	0.1033	-0.626	**-4.6422**	**-1.7737**	**-5.7968**		
	3	1.8101	0.3287	0.6751	0.6259	0.3273	-0.2726	**3.4876**	**1.7716**	**2.333**		
LAND	LOW*	0.4331	0.1038		0.6433	0.2325		-1.3135	-0.5912		4.1942	0.65
	MEDIUM	0.9414	0.2706	0.5083	-0.7350	-0.5373	-1.3783	**-2.9138**	**-1.5612**	**-1.6003**		
	HIGH	-1.3744	-0.2017	-1.8075	0.0917	0.0299	-0.5516	**4.2274**	**1.8254**	**5.5409**		
PROD	LOW*	-0.4029	-0.2011		-0.6511	-0.3955		-0.0342	-0.0267		2.5932	0.86
	MEDIUM	0.8025	0.3679	1.2054	0.1551	0.1066	0.8062	2.4953	-1.2608	2.5295		

HIGH	-0.3996	-0.1175	0.0033	0.4960	0.2737	1.1471	2.5295	1.4880	2.5637		
PRICE	-0.0475	-0.3097		**-0.2005**	**-2.0103**		**-0.2114**	**-2.0817**		6.7985	0.079
SCALE MODEL PARAMETERS											
sClass1 (ln λ_1)	0.000									117.4987	0.000
sClass2 (ln λ_2)	**-2.8026**	**-10.8397**									
sCLASS SIZE											
sClass1	0.5249										
sClass2	0.4751										
CLASS AND SCLASS SIZES											
Sclass	1	1	1	2	2	2					
Class	1	2	3	1	2	3					
ClassSize	0.3515	0.1712	0.0022	0.0035	0.1051	0.3665					
CLASS AND SCLASS COVARIANCES/ASSOCIATIONS											
sclass(1)<-> Class(1)	0.0000									29,7370	0.000
sclass(1)<-> Class(2)	0.0000										
sclass(1)<-> Class(3)	0.0000										
sclass(2)<-> Class(1)	**-4.6134**	**-5.0768**									
sclass(2)<-> Class(2)	**-0.4875**	**-2.1486**									
sclass(2)<-> Class(3)	**5.1010**	**5.4065**									

[*] Base-level situation for the effects-coded attributes.

[a] Adjusted marginal utility gains from the base-level situation for the effects-coded attributes.

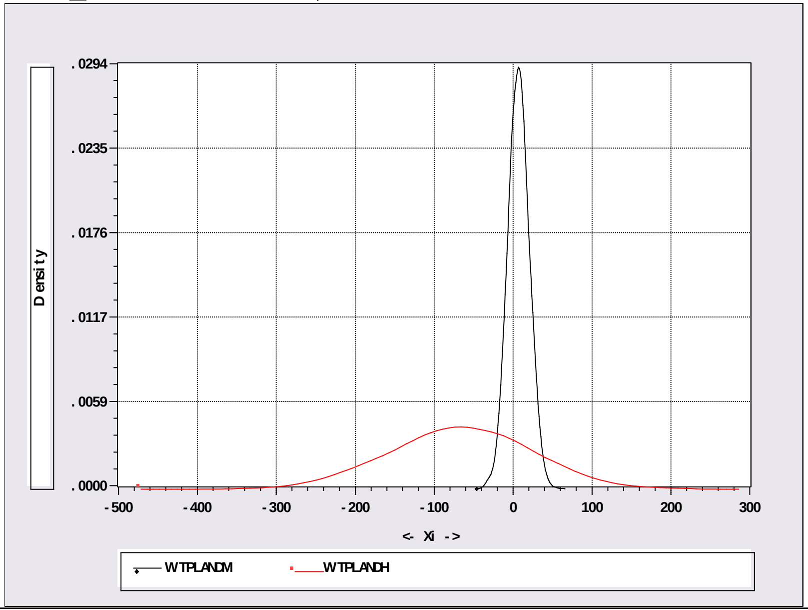
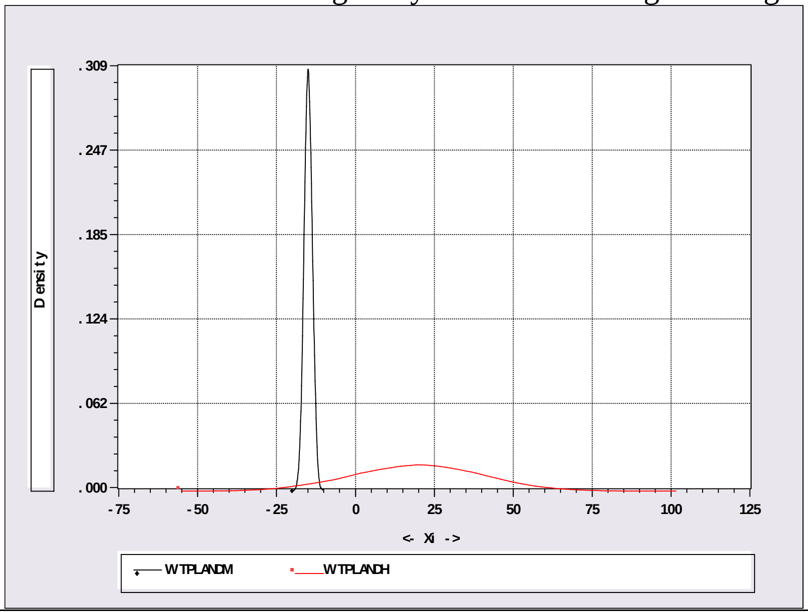
The marginal WTP estimates and the confidence intervals for the free allocation model are reported in Table 8 and Figure 2 while their counterparts for the deterministic model are reported in Table 9 and Figure 3, respectively. Unconditional mean estimates are obtained by averaging the mean WTP estimates across classes using posterior probabilities as weights and considering significance of estimates (Hensher et al., 2015). Inspecting these unconditional estimates, disparities across the two models are wide. For example, reducing the risk of breed extinction to low levels reduces the utility of respondents in the free allocation model so that respondents on average should be compensated for achieving it (-18.35 €/household) while in the deterministic allocation model this attribute level holds the highest contribution to increase respondents utility (93.92 €/household), mostly related to the high estimate obtains for this level by respondents in class 3. Another illustration of these differences across models are seen in estimates across model approaches arises in the indoor management attribute estimates, reporting significant and high disutility in the deterministic allocation model (-65.09 €/household) versus positive estimates retrieved in the free allocation model.

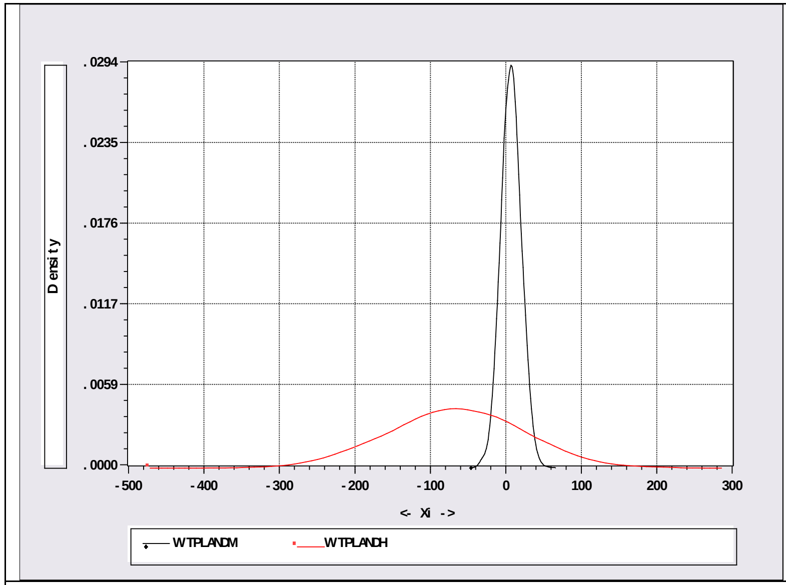
Table 8. Marginal Willingness to Pay estimates for the RLC free allocation and the confidence interval model (€/year household)

Attributes	Levels	Class 1		Class 2		Class 3		Unconditional mean estimates (considering class size and significance)
		Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean
EXIST	M_RISK	**-33.53****	(23,00; 44.93)	15.31	(-11.96; 41.92)	**122.97***	(90.89; 155.28)	9.60
	L_RISK	**-150.37****	(-143.79; -157.94)	**40.99*****	(17.24; 62.43)	**192.85****	(141.31; 243.00)	-24.09
MNG	OUT-IN DOOR	--67.66	(-86.34; --48.22)	-22.40	(-4.42; -41.03)	2.93	(-39.34; 42.16)	ns
	INDOOR	48.63	(31.00; 65.94)	**-42.84*****	(-24.84; -61.39)	**58.64****	(28.91; 91.19)	1.26
TSP	2	-78.84	(-63.18; -94.97)	**-35.87****	(-27.04; -44.36)	125.84	(74.78; 174.53)	-9.64
	3	-57.33	(-36.34; -77.90)	-28.45	(-22.47; -34.82)	**-3.94***	(-48.40; 41,71)	-0.86
LAND	MEDIUM	-16.00	(-2.44; -28.38)	-12.79	(4.04; -29.35)	**2.64****	(-29.87; 34.96)	0.58
	HIGH	18.13	(5.92; 31.45)	4.62	(-5.87; 15.52)	**-71.49****	(-22.81; 117.11)	-15.58
PROD	MEDIUM	-29.02	(-21.06; -37.19)	-8.48	(0.02; -17.35)	-82.15	(-7.05; -159.86)	ns
	HIGH	-22.54	(-12.21; -33.84)	-1.65	(-1.69; 8.19)	-65.07	(-15.22; 113.02)	ns

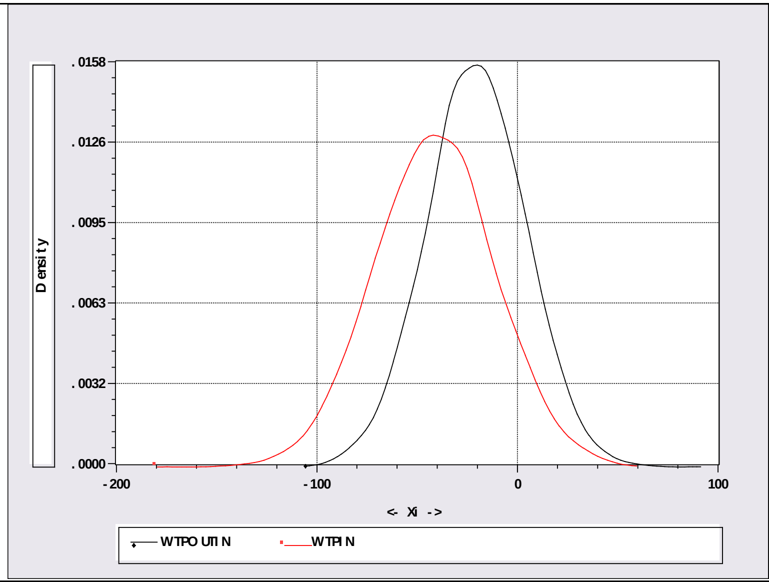
*p < 0.10 **p < 0.05 ***p < 0.01

Figure 2. Kernel density functions of mWTP (€/year household) estimates per attribute and class for **RLC free allocation** model for significant standard deviations in per class specific parameters.

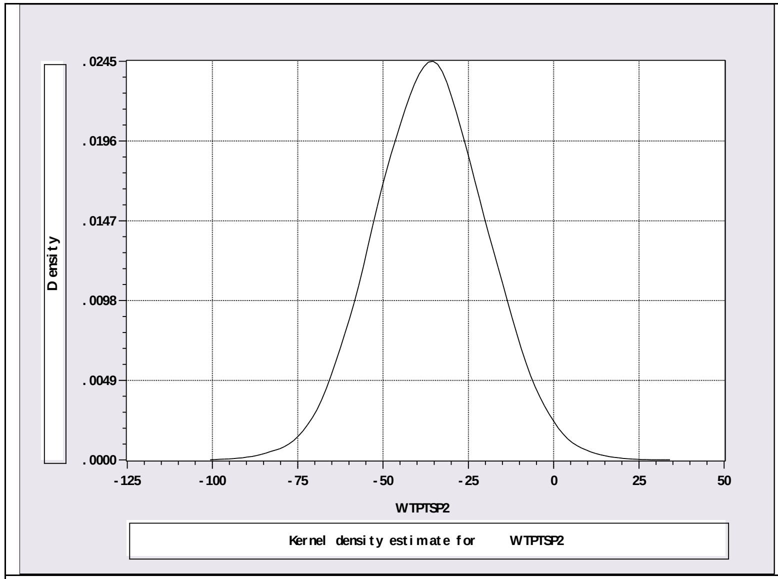
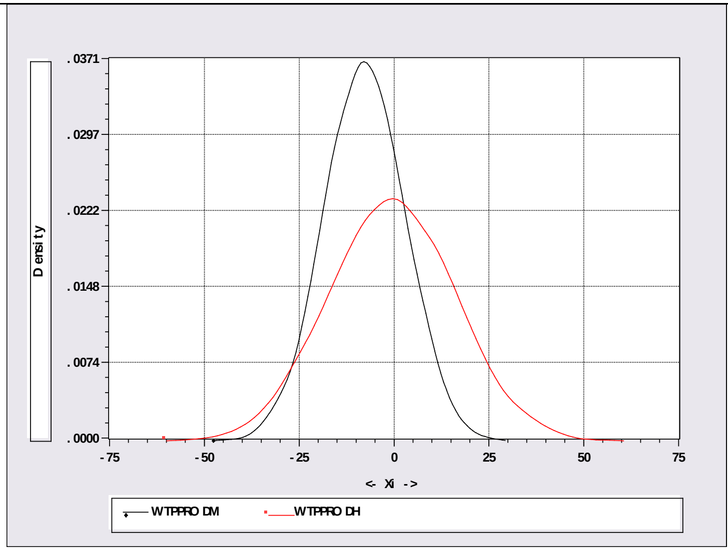
<table>
<tr><td colspan="2">CLASS 1</td></tr>
<tr><td>Type of management.
OUT_IN: 50% outdoors, 50% indoors IND: indoors

</td><td>Type of landscape
LANDM: medium heterogeneity LANDH: high heterogenity

</td></tr>
<tr><td colspan="2">CLASS 2</td></tr>
<tr><td>Breed existence
EXM: medium risk of extinction EXL: low risk of extinction</td><td>Type of management.
OUT_IN: 50% outdoors, 50% indoors IND: indoors</td></tr>
</table>

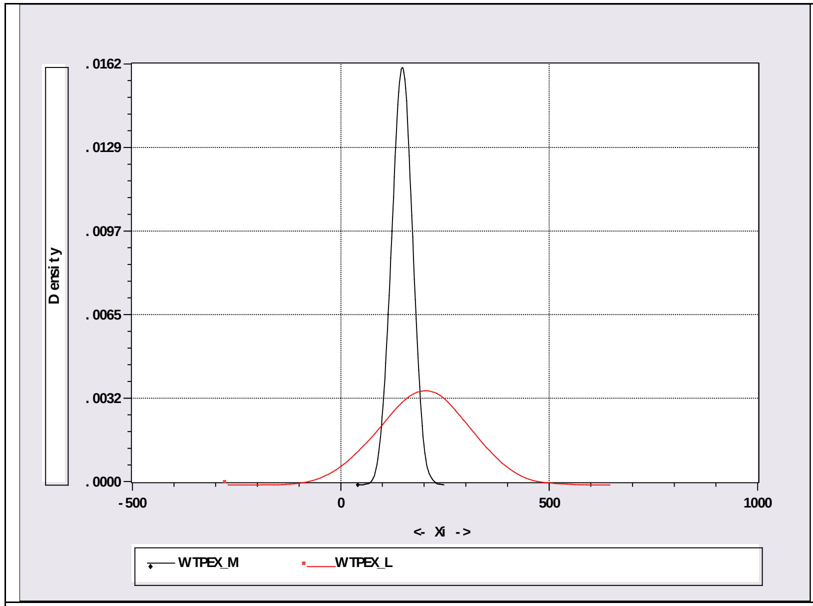


Tree crops
TSP2: 2 tree species, medium variety

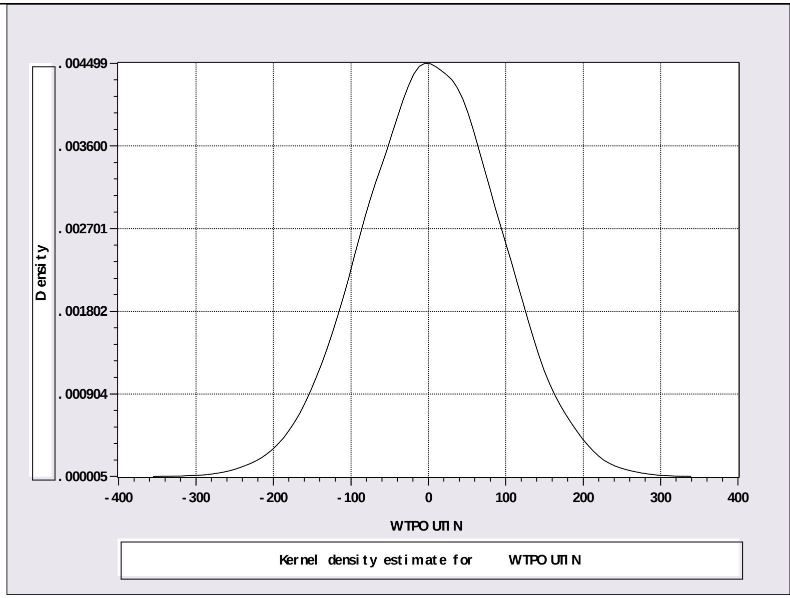


Product variety
PRODM: Medium product variety PRODH: High product variety

<table>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">CLASS 3</td></tr>
<tr><td>Breed existence
EXM: medium risk of extinction EXL: low risk of extinction</td><td>Type of management.
OUT_IN: 50% outdoors</td></tr>
</table>



Tree crops
TSP2: 2 tree species, medium variety TSP3: 3 species, high variety



Type of landscape
LANDM: medium heterogeneity LANDH: high heterogenity

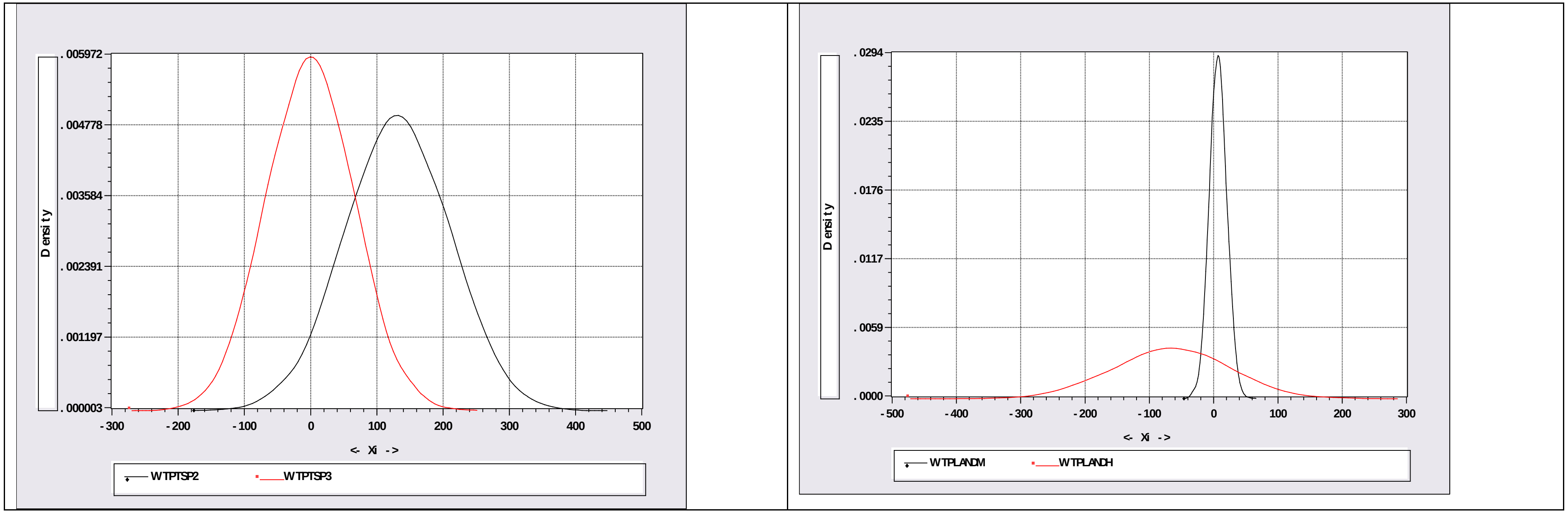


Table 9. Marginal Willingness to Pay estimates for the RLC deterministic protester allocation and the confidence interval model (€/year household)

Attributes	Levels	Class 2		Class 3		Unconditional mean estimates (considering class size and significance)
		Mean	95% CI	Mean	95% CI	Mean
EXIST	M_RISK	8.11	(-8.95; 26.73)	97.13	(32.73; 157.52)	ns
	L_RISK	7.48	(-18.51; 35.24)	**229.70***	(129.60; 325.85)	54.37
MNG	OUT-IN DOOR	**38.95****	(4.35; 75.02)	-60.52	(-83.29; -38.90)	15.90
	INDOOR	**-34.08****	(-71.97; 3.84)	**-216.11****	(-249.05; 184.62)	-65.07

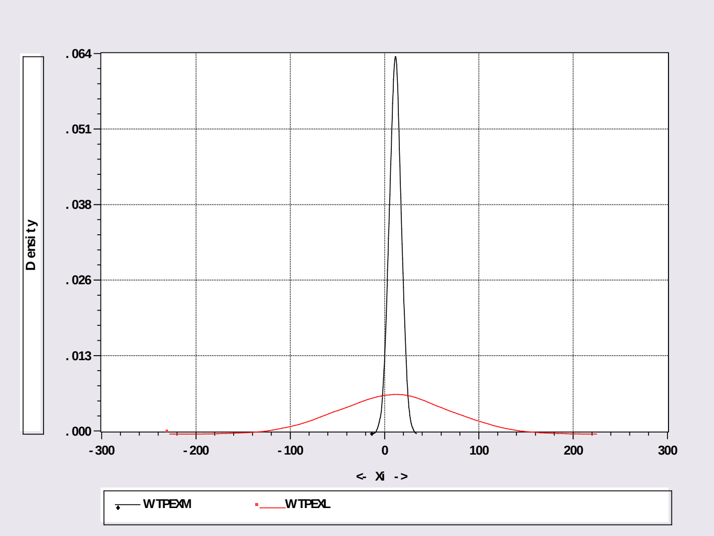
TSP	2	-33.24	(-43.90; 3.63)	-18.30	(-39.39; 6.99)	ns
	3	11.92	(-27.07; 3.13)	**57.22****	(27.51; 88.36)	13.54
LAND	MEDIUM	15.57	(-10.86; 42.81)	18.36	(-31.04; 63.44)	ns
	HIGH	-6.21	(-27.15; 14.32)	10.73	(-29.98; 48.33)	ns
PROD	MEDIUM	19.59	(-2.45; 44.68)	-15.53	(-394.75; 377.23)	ns
	HIGH	**50.45****	(20.05; 82.56)	-14.85	(-57.40; 29.38)	20.60

*p < 0.10 **p < 0.05 ***p < 0.01

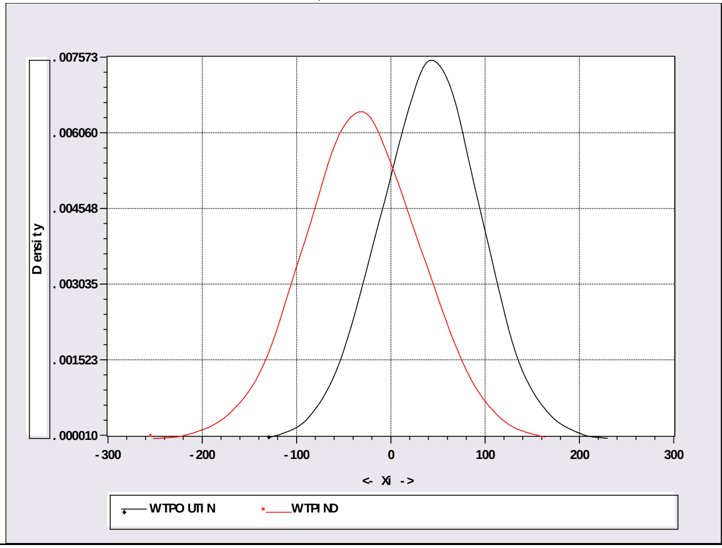
Figure 3. Dispersion of mWTP (€/year household) per attribute and class for **RLC deterministic allocation** model (dispersion for unconditional estimates only reported when standard deviation estimates are significant)

CLASS 2

Breed existence
EXM: medium risk of extinction EXL: low risk of extinction

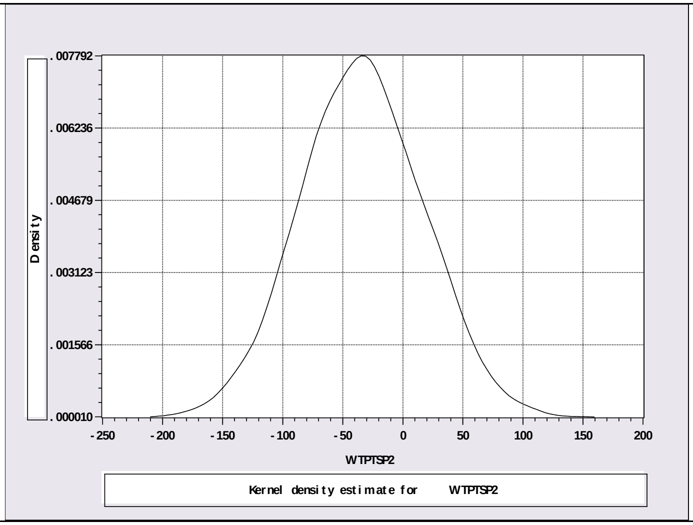


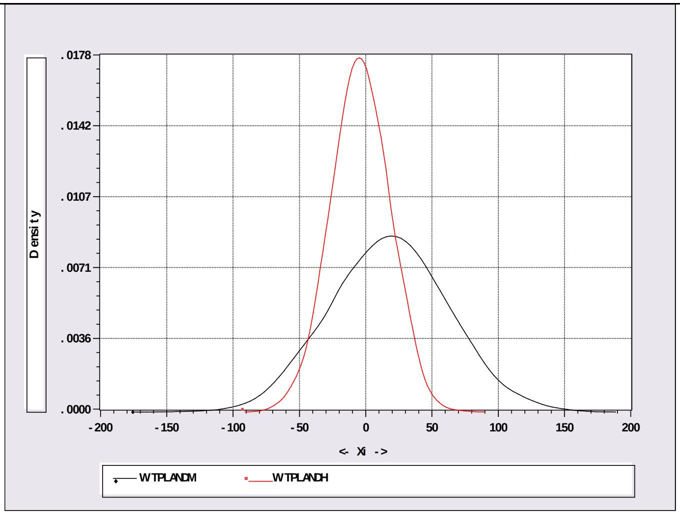
Type of management.
OUT_IN: 50% outdoors, 50% indoors IND: indoors



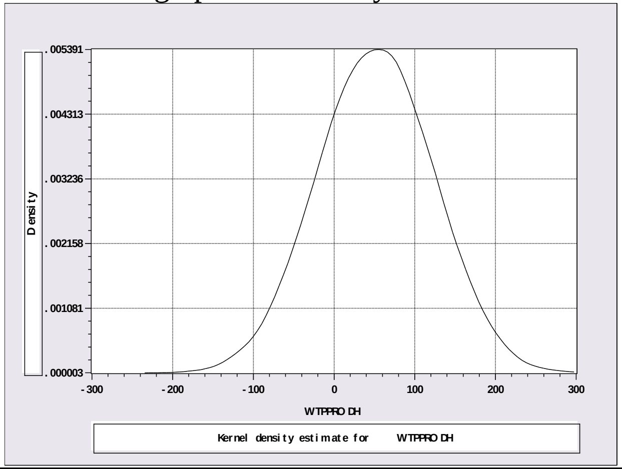
Tree crops
TSP2: 2 tree species, medium variety

Type of landscape
LANDM: medium heterogeneity LANDH: high heterogenity



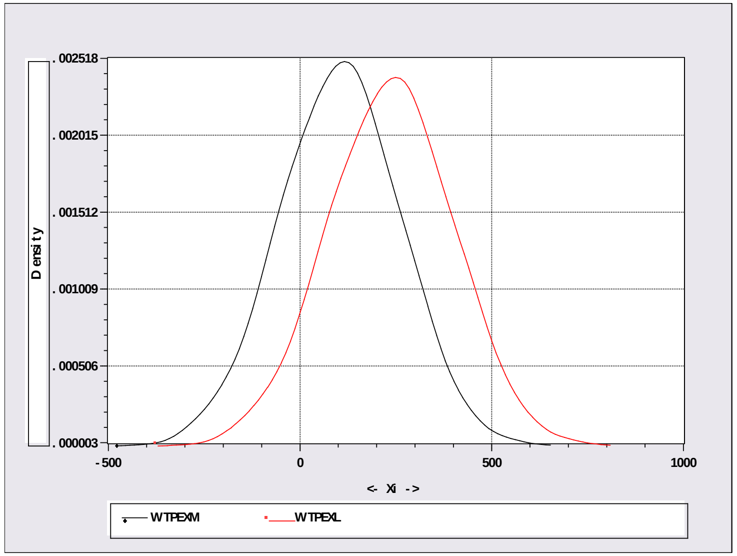


Product variety
PRODH: High product variety

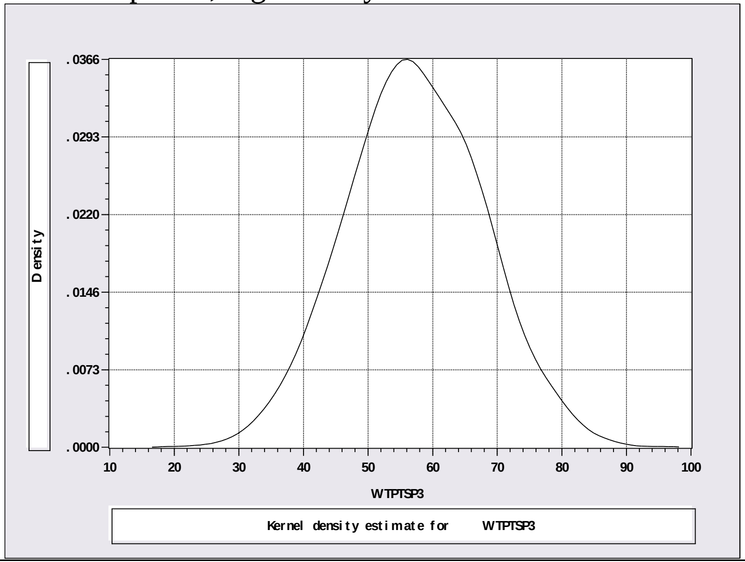


CLASS 3

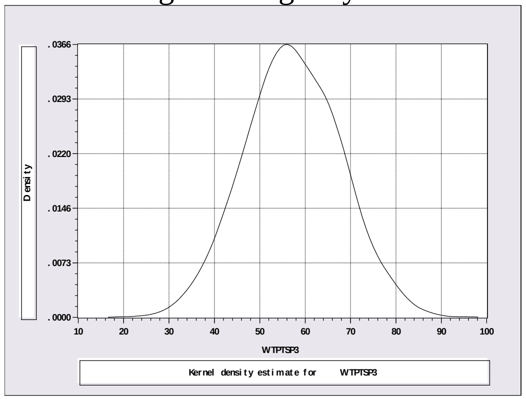
Breed existence
EXM: medium risk of extinction EXL: low risk of extinction



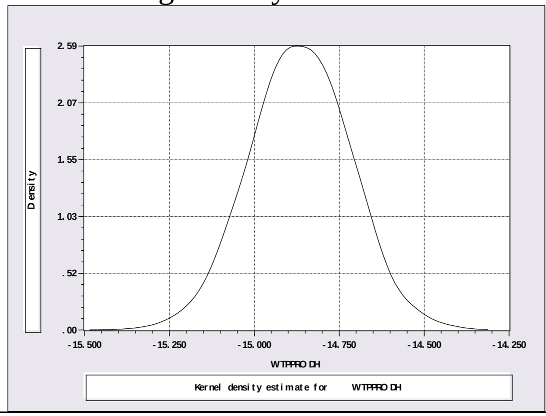
Tree crops
TSP3: 3 species, high variety



Type of landscape
LANDH: high heterogenity



Product variety
PRODH: high variety



1

5 Discussion and conclusions

5.1 Insights and trade-offs of the free vs. deterministic allocation approaches

Identifying and excluding protest responses from ulterior econometric modelling is a common practice in economic valuation studies. However, this can lead to sample selection and estimation bias, especially when the number of protest responses is high. In this study we compared two approaches to deal with protesters in modelling when discrete approaches are adopted. More specifically, we delve into the impact of free versus deterministic protest responses allocation on preferences and WTP estimates across two discrete modelling approaches, random parameters and SALC latent class models.

Deterministic allocation of protesters to one preference class comes at the cost of the reduction in model performance regarding information criteria. However, it provided more meaningful identification of preference profiles in the random parameter approach. In contrast, the estimates of the free allocated random LC model hinder a real segregation into preference classes as signalled by previous studies (Thiene et al., 2012). While protesters are typically characterized by non-significant estimates in any of the attributes and a general preference for the status quo expressed by the ASC. significant cost attribute estimates are retrieved for all the classes in this model together with misleading yea-saying patterns in class 3.

Free allocation models perform better in identifying serial status quo selection behaviour when scale heterogeneity is considered. The SALC model in this case retrieves patterns in preference class 1 that match with the expected protest behaviour although the share of respondents allocated to it amounts to approximately half of the sample.

The deterministic allocation of protesters provides overall better insights into preference profiles with similarities in preference patterns found between random parameters and scale-adjusted approaches, despite differences in class sizes across models. In both cases the non-protest classes are characterized by two distinct preference patterns. Class-2 respondents in both models show a narrower range of attributes that positively define their preferences, namely support for outdoor breed management together with high product variety in the random parameters model. Class-3 respondents in both models show a more balanced utility definition by a mix of attributes that include breed conservation, high tree crop diversity and either outdoor management (random parameters model) or landscape diversity (SALC model). The sclass2 respondents (these showing higher variance in their estimates) are mostly allocated to the third preference class.

SALC models in both free and deterministic protester allocation models show that the highest share of low scale (high variance) responses is found in preference segments with a wider set of attributes defining their preferences.

The disparities between estimates in the free vs. the deterministic model approach also impacts on the WTP estimates, leading to distinctively different policy recommendations based on these estimates. The free allocation model suggests that moderate improvement in the breed conservation status together with a shift towards indoor breeding are the path to maximize social utility. In contrast, the deterministic model advocates for focusing the efforts in breed conservation followed by improving product diversity and outdoor-indoor breeding with improvements in tree crop diversity. These outcomes, beyond the reasoning provided above, is also aligned with the results obtained in the world café sessions with rural and urban dwellers.

Therefore, our results advocate for and are aligned with the approach proposed by Thiene et al. (2012) where the allocation of protesters to a specific segment is preferred since reduction in model performance is compensated by a more plausible and balanced definition of the preference structure. Accordingly, the following sections in the discussion are based on the results of our preferred model, i.e. the random parameter latent class model with deterministic allocation of protesters to one preference class.

5.2 Societal preferences for MBP farming system dimensions

LC analysis allowed us to identify relevant preference profiles where respondents in class2 are concerned with management and product innovation. We hypothesize that the tight link established by participants in focus groups between management and product quality may be behind this preference profile that groups the so to speak pragmatic respondents that are more appealed by market-based solutions and these to succeed need quality-based products. By contrast, the preferences of respondents in class 3, the breed-concerned class, are more linked to heritage dimensions that connect with elements of the breed, its management and linked landscape. We also hypothesize that these respondents may hold moral concerns that can depart to some extent from their economic rationality when expressing their preferences for breed conservation. Accordingly, their preferences mostly shaped by improving the breed status maintaining traditional management and improved tree crop diversity. Classes 2 and 3 show complementary patterns of the significance of WTP estimates: only the rejection of indoor breeding retrieves significant and negative WTP values for both classes. We hypothesize that pragmatic reasons related to meat quality and welfare-heritage reasons are behind these preferences. .

Outcomes for reducing the risk of extinction of MBPs to the low status retrieve significant and positive estimates only in class3. Credibility problems may be behind the estimates because some of the respondents in the focus groups stated that breed extinction—for them—was unrealistic. Indoor management of the breed is significantly rejected by class2 and class3. Respondents stated in debriefing questions that the outdoors option was chosen for meat quality reasons (37.8% of the sample), followed by animal welfare concerns (24.5%).

The literature has demonstrated how landscape preferences have adopted virtual reality or manipulated pictures to assess social landscape preferences (Häfner et al., (2017), Arnberger and Eder, (2011) or van Berkel and Verburg (2014)). Although the pictures used to convey this attribute correspond to the central part of the island where the MBP agroecosystems are found, one of the weaknesses of our work relates to the pictures used because we did not fully control for landscape features through manipulated pictures. As kindly noticed by one of the reviewers, our method may have introduced bias into our estimates because some of the features in the pictures may represent differential recreational opportunities for some people and this may be the reason behind the non-significant estimates for this attribute across classes. Tree polycultures, by contrast, are positively evaluated by class3. Tree polyculture is tightly linked to the management and meat quality of MBPs, where a share of the tree fruit harvest feeds MBPs and provides its meat with outstanding qualities.

Traditional food products constitute a critical element of European culture, identity, and heritage (Ilbery y Kneafsey, 1999) and may contribute to the sustainability of rural areas because their product differentiation may entail a potential for producers and processers and hence contribute to creating business models that protect these areas from depopulation (Avermaete et al., 2004).

Sobrassada, the spreadable cured sausage produced with MBP meat carcass, is a traditional food product according to the definition of Gellynck and Kühne (2008). However, as some participants stated in the world café session, its niche in the market has decreased due to its high fat content. The special qualities of MBP meat appeal to niche buyers, and market extension through product innovation may command a substantial price premium compared with mainstream alternative products (Balogh et al., 2016). Innovations in traditional products may represent an opportunity to widen their market (Kühne et al., 2010) and hence represent an opportunity to increase the added value of farm production through the 'demand-side'.

However, innovations in traditional products may face challenges related to the possible incongruence between the concepts of traditional food and innovation (Guerrero et al., 2012; Stolzenbach et al., 2013), which makes launching acceptable innovations particularly difficult in this food category (Vanhonacker et al., 2013). One of the dimensions of innovation in traditional food products recognised by consumers relates to product variety (Guerrero et al., 2009). We tested the social acceptability for innovation in MBP product variety and similar to the literature (Guerrero et al., 2009), we found a positive attitude towards variety among the respondents that significantly supports high product variety options in the class2 segment. New MBP products such as hamburgers have shown highly relevant sensory performance (Kallas et al., 2019), and this finding may reinforce it as a promising innovation avenue because sensory properties are not compromised but enhanced by the innovation.

5.3 Policy implications for supporting extensive farming systems

Breeds in marginal areas and that may thrive in low external input agriculture represent a critical genetic resource in terms of adaptive traits and of rendering marginal lands economically viable (Gandini y Villa, 2003; Hoffmann y Scherf, 2010). Protection of conservation values tied to traditional breeds and cultural landscapes calls for approaches that directly target agricultural policy and integrate effective support for low-intensity use.

However, intensification processes have been catalysed by the CAP (Emmerson et al., 2016), accelerating the reduction of mixed farms (Agrosynergie 2011) such as traditional farms where MBPs constitute approximately 20% of farm income (Jaume comm. pers.). Despite the restructuring of the CAP following Agenda 2000, which acknowledged that farming activities have productive and non-productive functions, payments are not having the expected positive impacts in terms of increasing the workforce and securing balanced territorial development (Navarro y López-Bao, 2018). Policy measures created to support specific traditional land uses and their landscapes are often not successful because they focus on only one part of the system (Pinto-Correia et al., 2016) and are poorly tailored to fit marginal extensive systems where most farmers are not eligible for support (Pe'er et al., 2017). To overcome this situation and improve the future sustainability of these farming systems and the cost and environmental effectiveness of CAP payments, these measures should be linked to environmental objectives (Navarro y López-Bao, 2018).

Unconditional WTP estimates retrieved in our study signal societal support for policies aimed at improving the status of the breed and its management systems. The highest WTP estimates in our sample reside in securing breed low risk of extinction, increasing the product variety and in the outdoor management with some indoor sheltering.

Increased market orientation of farming in the European Union (EU) stimulated by CAP has the effect of exposing EU producers to more volatile world market prices compared with the politically fixed EU prices of the past (Pe'er et al., 2017), where livestock keepers are mere price-takers in a global economy where information asymmetry and market imperfections have implications for breed diversity (Hoffmann y Scherf, 2010).

Sustainable production systems depend on, in terms of markets, the maintenance of the characteristics of the final products and the defence of its genuineness (Silva y Nunes, 2013). Marketing extensively reared slaughtered pigs through the regular pathway would retrieve almost zero economic gains because the carcasses do not conform to EU standards and would hence be considered qualitatively inferior (Hill et al., 2004).

Because sustainable pig production systems in the Mediterranean region show marked differences in relation to technologies and final products arising from intensive systems (Silva y Nunes, 2013), developing alternative (and complex) marketing strategies is necessary in parallel with a consumer informed of the advantages of the outdoor keeping system and resulting quality of the product (Hill et al., 2004). Our results indicate societal support for innovation in traditional product variety and may represent an opportunity to increase the value added appraised by MBP farmers and hence contribute to the sustainability of this traditional farming system.

5.4 Limitations of our research and future pathways

Protest behaviour in choice experiment studies has been broadly assessed in the literature as discussed previously. Our study tackles the modelling perspective of it since the share of protest respondents in our study was considerable and simply excluding these observations would necessarily lead to biased estimates. Despite potential protest behaviour was identified in world café sessions and it was tackled offering different options for the payment vehicle to the respondents, the share of protesters remained still relatively high. Our study tackles the modelling perspective and implications of it, but one of the limitations of our study resides in the limited perspective that debriefing questions offer on this behaviour. Greater understating of it would be needed. We also consider that some institutional distrust may be behind a substantial share of this behaviour (Kassahun et al., 2020), but we did not test for it.

Another potential limitation on our work resides on the description of the landscape attribute and its levels, where artificially manipulated pictures or even virtual reality ones would have allowed for a more homogeneous delivery of this attribute to the respondents. The lack of significance of this attribute and its levels in almost all the models estimated may also be due to this limitation and not solely to its lack of significance in shaping people's preferences.

Acknowledgements

6 Bibliography

Adamowicz, W., Boxall, P., Williams, M., Louviere, J., 1998. Stated preference approaches for measuring passive use values: choice experiments and contingent valuation. Am. J. Agric. Econ. 80, 64-75.

Anderson, S., 2003. Animal genetic resources and sustainable livelihoods. Ecol. Econ. 45, 331-339. https://doi.org/10.1016/S0921-8009(03)00088-0

Andrews, R.L., Currim, I.S., 2003. A Comparison of Segment Retention Criteria for Finite Mixture Logit Models. J. Mark. Res. 40, 235-243. https://doi.org/10.1509/jmkr.40.2.235.19225

Aparicio Tovar, M.A., Vargas Giraldo, J.D., 2006. Considerations on ethics and animal welfare in extensive pig production: Breeding and fattening Iberian pigs. Livest. Sci. https://doi.org/10.1016/j.livsci.2006.05.010

Avermaete, T., Viaene, J., Morgan, E.J., Pitts, E., Crawford, N., Mahon, D., 2004. Determinants of product and process innovation in small food manufacturing firms. Trends food Sci. Technol. 15, 474-483.

Balogh, P., Békési, D., Gorton, M., Popp, J., Lengyel, P., 2016. Consumer willingness to pay for traditional food products. Food Policy 61, 176-184. https://doi.org/10.1016/J.FOODPOL.2016.03.005

Bauer, D.M., Johnston, R.J., 2013. The economics of rural and agricultural ecosystem services: purism vs practicality. Agric. Resour. Econ. Rev. 42, iii-xv.

Beaufoy, G., Cooper, T., 2008. Guidance document to the Member States on the application of the High Nature Value impact indicator. Brussels.

Bellon, M., 2009. Do we need crop landraces for the future? Realizing the global option value of in-situ conservation., en: Kontoleon, A., Pascual, U., Smale, M. (Eds.), Agrobiodiversity Conservation and Economic Development. Routledge, Abingdon, UK, pp. 56-72.

Bernués, A., Rodríguez-Ortega, T., Ripoll-Bosch, R., Alfnes, F., 2014. Socio-cultural and economic valuation of ecosystem services provided by Mediterranean mountain agroecosystems. PLoS One 9, e102479. https://doi.org/10.1371/journal.pone.0102479

Bernués, A., Ruiz, R., Olaizola, A., Villalba, D., Casasús, I., 2011. Sustainability of pasture-based livestock farming systems in the European Mediterranean context: Synergies and trade-offs. Livest. Sci. 139, 44-57. https://doi.org/10.1016/j.livsci.2011.03.018

Boxall, P., Adamowicz, W.L., Moon, A., 2009. Complexity in choice experiments: Choice of the status quo alternative and implications for welfare measurement. Aust. J. Agric. Resour. Econ. https://doi.org/10.1111/j.1467-8489.2009.00469.x

Boxall, P.C., Adamowicz, W.L., 2002. Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach. Environ. Resour. Econ. 23, 421-446. https://doi.org/10.1023/a:1021351721619

Bujosa, A., Riera, A., Hicks, R.L., 2010. Combining Discrete and Continuous Representations of Preference Heterogeneity: A Latent Class Approach. Environ. Resour. Econ. 47, 477-493. https://doi.org/10.1007/s10640-010-9389-y

Burke, P.F., Aubusson, P.J., Schuck, S.R., Buchanan, J.D., Prescott, A.E., 2015. How do early career teachers value different types of support? A scale-adjusted latent class choice model. Teach. Teach. Educ. https://doi.org/10.1016/j.tate.2015.01.005

Burton, M., Rigby, D., 2009. Hurdle and latent class approaches to serial non-participation in choice models. Environ. Resour. Econ. https://doi.org/10.1007/s10640-008-9225-9

Cooper, T., Hart, K., Baldock, D., 2009. Provision of public goods through agriculture in the European Union. London.

Dale, V.H., Polasky, S., 2007. Measures of the effects of agricultural practices on ecosystem services. Ecol. Econ. 64, 286-296. https://doi.org/10.1016/j.ecolecon.2007.05.009

Emmerson, M., Morales, M.B., Oñate, J.J., Batáry, P., Berendse, F., Liira, J., Aavik, T., Guerrero, I., Bommarco, R., Eggers, S., 2016. How agricultural intensification affects biodiversity and ecosystem services, en: Advances in Ecological Research. Elsevier, pp. 43-97.

Farizo, B.A., Joyce, J., Soliño, M., 2014. Dealing with Heterogeneous Preferences Using Multilevel Mixed Models. Land Econ. 90, 181-198.

Fisher, B., Kerry Turner, R., 2008. Ecosystem services: Classification for valuation. Biol. Conserv. 141, 1167-1169. https://doi.org/http://dx.doi.org/10.1016/j.biocon.2008.02.019

Gandini, G.C., Villa, E., 2003. Analysis of the cultural value of local livestock breeds: a methodology. J. Anim. Breed. Genet. 120, 1-11.

Gellynck, X., Kühne, B., 2008. Innovation and collaboration in traditional food chain networks. J. Chain Netw. Sci. 8, 121-129.

Gonzalez, J., Jaume, J., Fàbrega, E., Gispert, M., Gil, M., Oliver, A., Llonch, P., Guàrdia, M.D., Realini, C.E., Arnau, J., Tibau, J., 2013. Majorcan Black Pig as a traditional pork production system: Improvements in slaughterhouse procedures and elaboration of pork carpaccio as an alternative product. Meat Sci. https://doi.org/10.1016/j.meatsci.2013.03.012

Greene, W.H., Hensher, D.A., 2013. Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. Appl. Econ. 45, 1897-1902.

Guerrero, L., Claret, A., Verbeke, W., Vanhonacker, F., Enderli, G., Sulmont-Rossé, C., Hersleth, M., Guàrdia, M.D., 2012. Cross-cultural conceptualization of the words Traditional and Innovation in a food context by means of sorting task and hedonic evaluation. Food Qual. Prefer. 25, 69-78.

Guerrero, L., Guàrdia, M.D., Xicola, J., Verbeke, W., Vanhonacker, F., Zakowska-Biemans, S., Sajdakowska, M., Sulmont-Rossé, C., Issanchou, S., Contel, M., Scalvedi, M.L., Granli, B.S., Hersleth, M., 2009. Consumer-driven definition of traditional food products and innovation in traditional foods. A qualitative cross-cultural study. Appetite 52, 345-354. https://doi.org/10.1016/J.APPET.2008.11.008

Hajjar, R., Jarvis, D.I., Gemmill-Herren, B., 2008. The utility of crop genetic diversity in maintaining ecosystem services. Agric. Ecosyst. Environ. 123, 261-270. https://doi.org/10.1016/j.agee.2007.08.003

Hess, S., Bierlaire, M., Polak, J.W., 2007. A systematic comparison of continuous and discrete mixture models. Eur. Transp.

Hill, B.T., Beinlich, B., Köstermeyer, H., Dieterich, M., Neugebauer, K., 2004. The pig grazing project: Prospects of a novel management tool, en: Cultural Landscapes and Land Use. Springer, pp. 193-208.

Hoffmann, I., Scherf, B., 2010. Implementing the Global plan of action for animal genetic resources. Anim. Genet. Resour. génétiques Anim. genéticos Anim. 47, 1-10.

Hoyos, D., Mariel, P., Pascual, U., Etxano, I., 2012. Valuing a Natura 2000 network site to inform land use options using a discrete choice experiment: An illustration from the Basque Country. J. For. Econ. 18, 329-344. https://doi.org/10.1016/j.jfe.2012.05.002

Hynes, S., Campbell, D., 2011. Estimating the welfare impacts of agricultural landscape change in Ireland: a choice experiment approach. J. Environ. Plan. Manag. 54, 1019-1039. https://doi.org/10.1080/09640568.2010.547691

Hynes, S., Hanley, N., Scarpa, R., 2008. Effects on welfare measures of alternative means of accounting for preference heterogeneity in recreational demand models. Am. J. Agric. Econ. 90, 1011-1027.

Ilbery, B., Kneafsey, M., 1999. Niche markets and regional speciality food products in Europe: towards a research agenda. Environ. Plan. A 31, 2207-2222.

Jaume, J., Alfonso, L., 2000. The Majorcan Black pig. Anim. Genet. Resour. Inf. https://doi.org/10.1017/s1014233900001292

Jeanloz, S., Lizin, S., Beenaerts, N., Brouwer, R., Van Passel, S., Witters, N., 2016. Towards a more structured selection process for attributes and levels in choice experiments: A study in a Belgian protected area. Ecosyst. Serv. 18, 45-57. https://doi.org/10.1016/j.ecoser.2016.01.006

Jorgensen, B.S., Syme, G.J., 2000. Protest responses and willingness to pay: Attitude toward paying for stormwater pollution abatement. Ecol. Econ. https://doi.org/10.1016/S0921-8009(99)00145-7

Justes, A., Barberán, R., Farizo, B.A., 2014. Economic valuation of domestic water uses. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2013.11.113

Kahneman, D., Knetsch, J.L., Thaler, R.H., 1991. Anomalies: Endowment effect, loss aversion, status quo bias. J. Econ. Perspect.

Kallas, Z., Varela, E., Čandek-Potokar, M., Pugliese, C., Cerjak, M., Tomažin, U., Karolyi, D., Aquilani, C., Vitale, M., Gil, J.M., 2019. Can innovations in traditional pork products help thriving EU untapped pig breeds? A non-hypothetical discrete choice experiment with hedonic evaluation. Meat Sci. https://doi.org/10.1016/j.meatsci.2019.04.011

Kamakura, W.A., Russell, G.J., Russell, J., 1989. A probabilistic choice model for Market Segmentation and Elasticity Structure.pdf. J. Mark. Res.

Kassahun, H., Swait, J., Jacobsen, J.B., 2020. Distortions in willingness-to-pay for public goods induced by endemic distrust in institutions. ResearchGate Preprint. DOI: https://doi.org/10.13140/RG.2.2.22144.99843

Kroeger, T., Casey, F., 2007. An assessment of market-based approaches to providing ecosystem services on agricultural lands. Ecol. Econ. 64, 321-332. https://doi.org/10.1016/j.ecolecon.2007.07.021

Kühne, B., Vanhonacker, F., Gellynck, X., Verbeke, W., 2010. Innovation in traditional food products in Europe: Do sector innovation activities match consumers' acceptance? Food Qual. Prefer. 21, 629-638. https://doi.org/10.1016/J.FOODQUAL.2010.03.013

Ladenburg, J., Olsen, S.B., Nielsen, R.C.F., 2007. Reducing hypothetical bias in choice experiments: testing an opt-out reminder, en: EAERE 2007 Annual Conference.

Louviere, J.J., Hensher, D.A., Swait, J.D., 2000. Stated Choice Method. Analysis and Application.

Lusk, J.L., Roosen, J., Fox, J.A., 2003. Demand for beef from cattle administered growth hormones or fed genetically modified corn: a comparison of consumers in France, Germany, the United Kindom, and the United States. Am. J. Agric. Econ. 85, 16-29.

Lutzeyer, S., Phaneuf, D.J., Taylor, L.O., 2018. The amenity costs of offshore wind farms: Evidence from a choice experiment. Energy Econ. 72, 621-639. https://doi.org/10.1016/J.ENECO.2018.03.020

Marull, J., Tello, E., Fullana, N., Murray, I., Jover, G., Font, C., Coll, F., Domene, E., Leoni, V., Decolli, T., 2015. Long-term bio-cultural heritage: exploring the intermediate disturbance hypothesis in agro-ecological landscapes (Mallorca, c. 1850--2012). Biodivers. Conserv. 24, 3217-3251. https://doi.org/10.1007/s10531-015-0955-z

Meyerhoff, J., Liebe, U., 2009. Status Quo Effect in Choice Experiments: Empirical Evidence on Attitudes and Choice Task Complexity. Land Econ. 85, 515-528. https://doi.org/10.3368/le.85.3.515

Meyerhoff, J., Liebe, U., Hartje, V., 2009. Benefits of biodiversity enhancement of nature-oriented silviculture: Evidence from two choice experiments in Germany. J. For. Econ. 15, 37-58.

Meyerhoff, J., Mørkbak, M.R., Olsen, S.B., 2014a. A Meta-study Investigating the Sources of Protest Behaviour in Stated Preference Surveys. Environ. Resour. Econ. https://doi.org/10.1007/s10640-013-9688-1

Meyerhoff, J., Mørkbak, M.R., Olsen, S.B., 2014b. A Meta-study Investigating the Sources of Protest Behaviour in Stated Preference Surveys. Environ. Resour. Econ. 58, 35-57. https://doi.org/10.1007/s10640-013-9688-1

Morrison, M.D., Blamey, R.K., Bennett, J.W., 2000. Minimising payment vehicle bias in contingent valuation studies. Environ. Resour. Econ. https://doi.org/10.1023/A:1008368611972

Narloch, U., Drucker, A.G., Pascual, U., 2011. Payments for agrobiodiversity conservation services for sustained on-farm utilization of plant and animal genetic resources. Ecol. Econ. 70, 1837-1845. https://doi.org/10.1016/j.ecolecon.2011.05.018

Nautiyal, S., Bisht, V., Rao, K.S., Maikhuri, R.K., 2008. The role of cultural values in agrobiodiversity conservation: a case study from Uttarakhand, Himalaya. J. Hum. Ecol 23, 1-6.

Navarro, A., López-Bao, J.V., 2018. Towards a greener Common Agricultural Policy. Nat. Ecol. Evol. 2, 1830.

Nijnik, M., Zahvoyska, L., Nijnik, A., Ode, A., 2009. Public evaluation of landscape content and change: Several examples from Europe. Land use policy 26, 77-86.

Pe'er, G., Dicks, L. V., Visconti, P., Arlettaz, R., Báldi, A., Benton, T.G., Collins, S., Dieterich, M., Gregory, R.D., Hartig, F., Henle, K., Hobson, P.R., Kleijn, D., Neumann, R.K., Robijns, T., Schmidt, J., Shwartz, A., Sutherland, W.J., Turbé, A., Wulf, F., Scott, A. V., 2014. EU agricultural reform fails on biodiversity. Science (80-.). https://doi.org/10.1126/science.1253425

Pe'er, G., Lakner, S., Müller, R., Passoni, G., Bontzorlos, V., Clough, D., Moreira, F., Azam, C., Berger, J., Bezak, P., Bonn, A., Hansjürgens, B., Hartmann, L., Kleemann, J., Lomba, A., Sahrbacher, A., Schindler, S., Schleyer, C., Schmidt, J., Schüler, S., Sirami, C., von Meyer-Höfer, M., Zinngrebe, Y., Herzog, F., Möckel, S., Benton, T., Dicks, L., Hart, K., Hauck, J., Sutherland, W., Irina Herzon, B., Matthews, A., Oppermann, R., Von Cramon-Taubadel, S., Deutschland, N., 2017. Is the CAP Fit for purpose? An evidence-based fitness-check assessment, German Centre for Integrative Biodiversity Research (iDiv). https://doi.org/Environment

Pinto-Correia, T., Guiomar, N., Guerra, C.A., Carvalho-Ribeiro, S., 2016. Assessing the ability of rural areas to fulfil multiple societal demands. Land use policy 53, 86-96. https://doi.org/10.1016/j.landusepol.2015.01.031

Provencher, B., Bishop, R.C., 2004. Does accounting for preference heterogeneity improve the forecasting of a random utility model? A case study. J. Environ. Econ. Manage. 48, 793-810. https://doi.org/http://dx.doi.org/10.1016/j.jeem.2003.11.001

Samuelson, W., Zeckhauser, R., 1988. Status quo bias in decision making. J. Risk Uncertain. https://doi.org/10.1007/BF00055564

Scarpa, R., Ferrini, S., Willis, K., 2005. Performance of Error Component Models for Status-Quo Effects in Choice Experiments, en: Scarpa, R., Alberini, A. (Eds.), Applications of Simulation Methods in Environmental and Resource Economics. Springer Netherlands, Dordrecht, pp. 247-273. https://doi.org/10.1007/1-4020-3684-1_13

Scarpa, R., Thiene, M., 2011. Organic food choices and Protection Motivation Theory: Addressing the psychological sources of heterogeneity. Food Qual. Prefer. 22, 532-541. https://doi.org/10.1016/j.foodqual.2011.03.001

Scarpa, R., Thiene, M., 2005. Destination choice models for rock climbing in the Northeastern Alps: a latent-class approach based on intensity of preferences. Land Econ. 81, 426-444.

Silva, J.S., Nunes, J.L.T., 2013. Inventory and characterization of traditional Mediterranean pig production systems: advantages and constraints towards its development. Acta Agric. Slov. 61-67.

Soliño, M., Farizo, B.A., 2014. Personal Traits Underlying Environmental Preferences: A Discrete Choice Experiment. PLoS One 9, e89603. https://doi.org/10.1371/journal.pone.0089603

Stolzenbach, S., Bredie, W.L.P., Byrne, D. V, 2013. Consumer concepts in new product development of local foods: Traditional versus novel honeys. Food Res. Int. 52, 144-152.

Swait, J., 1994. A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. J. Retail. Consum. Serv. https://doi.org/10.1016/0969-6989(94)90002-7

Swinton, S.M., Lupi, F., Robertson, G.P., Hamilton, S.K., 2007. Ecosystem services and agriculture: Cultivating agricultural ecosystems for diverse benefits. Ecol. Econ. 64, 245-252. https://doi.org/10.1016/j.ecolecon.2007.09.020

Thiene, M., Meyerhoff, J., De Salvo, M., 2012. Scale and taste heterogeneity for forest biodiversity: Models of serial nonparticipation and their effects. J. For. Econ. https://doi.org/10.1016/j.jfe.2012.06.005

Thiene, M., Scarpa, R., Louviere, J.J., 2015. Addressing Preference Heterogeneity, Multiple Scales and Attribute Attendance with a Correlated Finite Mixing Model of Tap Water Choice. Environ. Resour. Econ. 62, 637-656. https://doi.org/10.1007/s10640-014-9838-0

Tibau, J., Torrentó, N., Quintanilla Aguado, R., González, J., Angels Oliver, M., Gil, M., Jaume, J., Batorek-Lukač, N., 2019. Negre Mallorquí (Majorcan Black) Pig, en: European Local Pig Breeds - Diversity and Performance. A study of project

TREASURE. IntechOpen. https://doi.org/10.5772/intechopen.84434

Tisdell, C., 2003. Socioeconomic causes of loss of animal genetic diversity: analysis and assessment. Ecol. Econ. 45, 365-376. https://doi.org/10.1016/S0921-8009(03)00091-0

Valasiuk, S., Czajkowski, M., Giergiczny, M., Żylicz, T., Veisten, K., Elbakidze, M., Angelstam, P., 2017. Are bilateral conservation policies for the Białowieża forest unattainable? Analysis of stated preferences of Polish and Belarusian public. J. For. Econ. 27, 70-79. https://doi.org/10.1016/J.JFE.2017.03.001

Vanhonacker, F., Kühne, B., Gellynck, X., Guerrero, L., Hersleth, M., Verbeke, W., 2013. Innovations in traditional foods: Impact on perceived traditional character and consumer acceptance. Food Res. Int. 54, 1828-1835. https://doi.org/10.1016/J.FOODRES.2013.10.027

Varela, E., Giergiczny, M., Riera, P., Mahieu, P.-A., Soliño, M., 2014a. Social preferences for fuel break management programs in Spain: a choice modelling application to prevention of forest fires. Int. J. Wildl. Fire 23, 281-289.

Varela, E., Jacobsen, J.B., Soliño, M., 2014b. Understanding the heterogeneity of social preferences for fire prevention management. Ecol. Econ. 106, 91-104. https://doi.org/10.1016/j.ecolecon.2014.07.014

Varela, E., Mahieu, P.A., Giergiczny, M., Riera, P., Soliño, M., 2014c. Testing the single opt-out reminder in choice experiments: An application to fuel break management in Spain. J. For. Econ.

Vermunt, J.K., 2008. Latent class and finite mixture models for multilevel data sets. Stat. Methods Med. Res. 17, 33-51.

Vermunt, J.K., Magidson, J., 2005. Technical guide for Latent GOLD 4.0: Basic and advanced. Belmont Stat. Innov. Inc.

William, H.G., David, A.H., 2013. Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. Appl. Econ. 45, 1897-1902.

Yoo, J., Ready, R.C., 2014. Preference heterogeneity for renewable energy technology. Energy Econ. https://doi.org/10.1016/j.eneco.2013.12.007

Zander, K.K., Drucker, A.G., 2008. Conserving what’s important: Using choice model scenarios to value local cattle breeds in East Africa. Ecol. Econ. 68, 34-45. https://doi.org/10.1016/j.ecolecon.2008.01.023

Zander, K.K., Signorello, G., De Salvo, M., Gandini, G., Drucker, A.G., 2013. Assessing the total economic value of threatened livestock breeds in Italy: Implications for conservation policy. Ecol. Econ. 93, 219-229. https://doi.org/10.1016/j.ecolecon.2013.06.002

Zhang, W., Ricketts, T.H., Kremen, C., Carney, K., Swinton, S.M., 2007. Ecosystem services and dis-services to agriculture. Ecol. Econ. 64, 253-260. https://doi.org/10.1016/j.ecolecon.2007.02.024

1