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UNDERSTANDING THE HETEROGENEITY OF SOCIAL PREFERENCES FOR FIRE PREVENTION MANAGEMENT

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Abstract

The forest area burnt annually in the European Mediterranean region has more than doubled since the 1970s. In these forests, the main preventive action consists of forest compartmentalization by fuel break networks, which entail high costs and sometimes significant negative impacts. While many studies look at public preferences for fire suppression, this study analyses the heterogeneity of social preferences for fire prevention. The visual characteristics of fire prevention structures are very familiar to respondents, but their management is unfamiliar, which raises specific attention in terms of analysing preference heterogeneity. A random parameter logit model revealed large heterogeneity and preference for traditional heavy machinery, maintaining linear unshaded fuel breaks at a high density. A latent class model showed that this may be reflected by a third of the population preferring lighter machinery and shaded irregular fuel breaks; a quarter of the population not treating the budget constraint as limiting, another quarter only being worried about the area burnt and the remaining group being against everything. Finally, a discrete mixture model revealed extreme preference patterns for the density of fuel breaks. These results are important for designing fire prevention policies that are efficient and acceptable by the population.

Additional keywords: Forest fires, fuel breaks, heterogeneity, choice modelling, random parameter logit, latent class model, discrete mixture model.

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1. Introduction

The ecosystem services provided by Mediterranean forests – such as protection against erosion or biodiversity conservation - are increasingly recognized (FAO, 2013). However, these services are under risk of degradation, with forest fires as the most important threat to Mediterranean forest ecosystems today (Ministry of Environment, 1998; Valbuena-Carabaña et al., 2010). Every year forest fires in the European Mediterranean region attract media attention and debate about forest management so as to minimize the environmental and social damages, in particular when villages and infrastructure are affected. The annual burnt area in the European Mediterranean region has more than doubled since the 1970s (Xanthopoulos et al., 2006). Farmland abandonment is regarded as one of the main drivers of this situation (Duguy et al., 2007; Loepfe et al., 2010; Pausas, 2004; Pausas et al., 2008; Vélez Muñoz, 2004) as the traditional rural mosaic that creates sufficient fuel fragmentation is becoming scarce. The build-up of large and continuous fuel beds facilitates fire spread (Loepfe et al., 2010; Pausas, 2004), and forest fires are expected to be aggravated by climate change and resultant longer dry summer periods (Mouillot et al. 2002, Morriondo et al. 2006, Pausas, 2004). The losses due to forest fires are not only related to ecosystems, but also to human lives and infrastructure, with a wide array of interrupted or diminished ecosystem services flowing to society (Barrio et al., 2007).

In the Mediterranean region, wildfire spread is mainly reduced through the forest compartmentalization by fuel break networks. These structures traditionally are linear strips where the trees are disposed of and the vegetation is removed down to the mineral soil with mechanical tools. The costs of creating and maintaining such networks are high and the negative impacts (landscape impact and soil erosion) can be locally significant. Therefore, some public agencies are testing new designs for these structures as well as alternative maintenance tools to lower both the negative impacts and the costs. Fire prevention plans are developed by public agencies and are mainly based on technical and budget criteria (De Castro et al., 2007). This may be the best strategy in so far that the differences in management are small, technical and not visible to the general public. However, fire prevention has large impacts on the visual perception of the landscape, and forest fires as an environmental problem attract much attention from the population (IESA/CSIC, 2007). Therefore, from a welfare economic point of view, public preferences for fire prevention should be taken into account when designing fire prevention strategies.

The influence of fire on the social value of forests was initially addressed in Vaux et al. (1984), where changes in recreational values were studied. Hesseln et al. (2004) and Starbuck et al. (2006) also pursed this research avenue. Somewhat related, other valuation studies focused on the estimation of citizens' WTP for protecting certain areas or reducing wildfire risk in the landscape as a whole (Loomis and González-Cabán, 1994; Loomis and González-Cabán, 1998; Riera and Mogas, 2004; Winter and Fried, 2001). In recent years, the focus has broadened to explore citizens' preferences for different strategies aimed at diminishing wildfire risk, such as mechanical fuel reduction, prescribed burning or biomass for energy (González-Cabán et al., 2007; González-Cabán et al., 2004; Kaval et al., 2007; Loomis and González-Cabán, 2008; Loomis et al., 2004; Loomis et al., 2005; Loomis et al., 2009; Soliño, 2010; Soliño et al. 2010 and 2012; Walker et al., 2007). Holmes et al. (2012) explore risk perception and assess the trade-offs between wildfire risk and damage in public fire prevention systems. Calkin et al. (2012) investigate the trade-offs fire managers are willing to make under competing strategic suppression objectives. The fire issue can also be explored in a broader context, assessing the trade-offs between fire prevention and many ecosystem services at the same time (Mavsar et al., 2013) as well as between fire and different climate-sensitive attributes (Riera et al., 2007).

Forest fires and fire prevention are complex issues, subject to a variety of perceptions and even different paradigms among the population (Absher et al., 2009; McCaffrey et al., 2012). In particular they are complex in the sense that while fire prevention is positive per se, it may have some impacts in the landscape that are unwanted; making the typical distinction of people who are environmentally concerned or not, less obvious. These kind of trade-offs are also of relevance in other environmental issues like green energy vs visual disamenities gained from wind turbines (Westerberg et al., 2013; Jensen et al., 2014) or access reductions to preserve wildlife (Jacobsen et al., 2012). In this context, accounting and exploring for heterogeneity and understanding different distributional aspects provides knowledge of who will be affected by a policy change, which can be relevant to resource managers and to policy analysis.

Two complementary approaches may be distinguished to tackle the issue of preference heterogeneity. The first consists in assessing the observable component of heterogeneity by incorporating explanatory variables in the choice models (Choi and Fielding, 2013). Interactions of specific socioeconomic covariates with either site attributes or alternative-specific constants allow the capture of the observable component of heterogeneity (Choi and Fielding, 2013; Hynes et al., 2008). Socio-demographic characteristics are useful for interpretation (Hess et al., 2005), although assumptions are indeed required in the selection of the variables employed for these interaction terms; the variables must be relevant to the choice context being examined and they must have acceptable explanatory power (Boxall and Adamowicz, 2002). Attitudinal characteristics are increasingly being used as criteria for population segmentation or as explanatory variables for econometric models (Choi and Fielding, 2013; Lundhede et al., 2014). Fire related valuation studies typically include socioeconomic covariates such as income, education or age (Loomis et al., 2009; Mavsar et al., 2013), but also attitudinal questions to gain insight on respondents' preferences. Fire related questions such as perceived fire danger, perceived fire frequency by the respondents (Kaval et al 2007), witnessing fires or experiencing the negative consequences of forest fires have proved to be significant in determining WTP for fire prevention or biomass reduction activities (Loomis, 2008; Walker et al., 2007).

A complementary approach to the previous consists in assessing the unobserved heterogeneity of preferences through the systematic component of utility. Random parameter logit models (RPL), latent class models (LC) and discrete mixture models (DM) are three ways of doing so (Birol et al., 2006; Campbell et al., 2014; Doherty et al., 2013; Morey et al., 2006; Provencher and Bishop, 2004; Train, 2009) and are applied in the current study. These modelling approaches may provide complementary views to understand the unobserved heterogeneity at different levels: average population, population classes and management attributes. This is of particular importance for fire prevention due to the characteristics hereof: both the measures and consequences are very concrete but while the consequences are very familiar to respondents, yet the measures are often not very familiar even if they have a high impact on the landscape, and consequently on people.

This study aims at assessing whether people are sensitive to changes in the current situation of forest fire prevention and whether heterogeneity exists among the population in their preferences for fuel break management issues. For that purpose, a choice experiment was conducted among citizens in the province of Málaga, (Andalusia, Spain), to explore social preferences for three main fire-related attributes in fuel break management: the cleaning technique, the design of these structures, and the density of the grid. Respondents were asked to trade these against a payment in order to derive welfare economic estimates.

By using different modelling approaches (RPL, LC and DM) for the assessment of heterogeneity together with the consideration of socioeconomic and attitudinal variables, we are able to unveil different preference patterns both at the attribute and at the population level that are relevant in assessing social preferences for fire prevention management. This is, to our knowledge, not previously analysed in the fire related literature yet highly relevant due to the scarcity of these studies in the Mediterranean context. Furthermore, it adds to the literature on modelling heterogeneity in environmental valuation studies by applying recently developed models and compare what can be said by each. This is especially important for the application here which is concrete and familiar in output, yet unfamiliar in measures.

2. Forest fires and fire prevention in the Mediterranean region

Paleoecological studies suggest that fires are natural in the Mediterranean region (Pausas et al., 2008). Nevertheless, the increase in the number of fires and burnt area during the 20th century sometimes surpasses the capacity of these ecosystems to recover after the fire (Pausas et al., 2008). The social demand for environmental protection together with the consideration of forest ecosystems as a public good impelled the launching of permanent protection programmes against forest fires (Vélez Muñoz, 2004). The efforts evolved towards a policy centred in emergency suppression measures, based on very sophisticated equipment with high costs. As a result, fire suppression capacity in southern European countries has been improved since the 1990s, allowing for a reduction in the burnt area in relatively easy fire seasons. However, fire suppression policies have shown their limited ability to remove the risk of major disasters when not coupled with appropriate fuel management strategies (Xanthopoulos, Caballero et al. 2006; Rigolot, Fernandes et al. 2009). The excessive focus on fire suppression instead of fire prevention resulted in reduced availability of financial resources for long term preventive actions (Montiel and San Miguel, 2009), which are less spectacular and need continuous maintenance over time. It is expected that this trend will slowly change in light of the widely recognized role that prevention plays in fire protection (Tàbara et al. 2003), being maybe the most effective approach to face wildfires (FAO, 2013). Not only the researchers or land managers, but also the society, are progressively demanding a shift towards fire prevention management (Moyano et al.,2006).

Fire prevention is a group of activities aimed at reducing or avoiding the probability that a fire starts and also at limiting its effects if it takes place (Vélez Muñoz, 2000). Fire prevention entails two complementary approaches: social and physical. The social dimension aims at diminishing the causes of anthropogenic fires (Martínez et al., 2009), while the physical fire prevention deals with the biomass for the purpose of modifying potential fire behaviour (Husari et al., 2006) by decreasing fire intensity (Martinson and Omi, 2003), wildfire severity, rate of spread and, therefore, the likelihood of extreme fire behaviour (Husari et al., 2006; Piñol et al., 2007; Reiner et al., 2009; Schmidt et al., 2008). It is the latter that is in focus in the present paper.

In the Mediterranean region, wildfire spread is mainly reduced through the forest compartmentalization by fuel break networks (Moreira et al., 2011). A fuel break is a strategically located wide strip on which a cover of dense, flammable vegetation has been permanently changed into one of reduced flammability (Green, 1977). In addition, they represent safety areas providing quick access and a higher probability of successfully supressing a wildland fire (Agee et al., 2000).

When launching a fire prevention programme, decisions are made on cleaning technique for the fuel break (e.g. brush cutting or prescribed burning), the fuel break design (e.g. linear or irregular) and the density of the grid, which could influence the expected annually burnt area. Research has indicated the opportuneness of social participation in resource management activities and specifically in fuel reduction efforts (Winter et al., 2004). Understanding citizens' attitudes towards current practices and proposed changes would improve the communication between resource professionals and citizens (Toman and Shindler, 2006). To do this we need to not only focus on the average citizen, but also on the heterogeneity among them.

3. Material and Methods

3.1 Survey design, case study description and data collection

Citizens' preferences for environmental and natural resource management have traditionally been studied by natural resource economists for several purposes (e.g. cost-benefit analysis, decision-making, welfare assessment, etc). Several choice modelling techniques (ranking, rating and discrete choice) have been developed to do this. In this study, data obtained from a ranking experiment to explore social preferences for three main fire-related attributes in fuel break management (Varela et al., 2014) was used as a discrete choice experiment using only the best rank as suggested by Caparrós et al. (2008).

The DCE attributes were: fuel break cleaning tools, fuel break design and density of the fuel break network (coupled with a reduction of the annual burnt area). Cleaning tools considered were scarification with angledozer, backpack brushcutting, controlled grazing and prescribed burning. Fuel break designs considered the four possible combinations of irregular/linear edges with the presence/absence of trees (shaded/unshaded designs). Finally the density attribute showed four levels of fuel break density coupled with expected burnt area. A monetary attribute was also included and conveyed to respondents through recurrent annual payments by an increase in regional taxes. The attributes and levels were selected after consultations with fire managers and fire researchers in Andalusia and the resulting attributes (Table 1) were conveyed to the respondents through pictures to facilitate their comprehension. Furthermore, three focus groups and two pilot tests with twenty potential respondents each were conducted to secure a good comprehension among potential respondents.

The valuation questionnaire counted on a warm-up section prior to the choice exercise consisting of: i) some attitudinal questions on forest fires ii) an introduction to the prevention of forest fires through the use of fuel breaks, iii) some information about fire behaviour, comparing the outcomes of a low intensity fire (where fuel breaks are more likely to fulfil their mission) versus a big forest fire (where the fire can easily breach through the fuel breaks) and iv) presentation of the attributes' levels with pros and cons related to each of those.

The choice sets utilized in our study were prepared following an optimal in difference design as proposed by Street et al. (2005) and Street and Burgess (2007). The design consisted of sixteen choice sets and each respondent was asked to evaluate all sixteen. Evaluating the d-error ex-ante for a multinomial main effect model gave a d-error of 0,008894. Choice cards showed an identical status quo option which corresponds to the current most widespread management in Málaga, (the province of Andalucía, Southern Spain) where the survey was conducted plus three alternative management programs. An example of the choice cards is shown in Figure 1[1].

[Table 1 around here]

[Figure 1 around here]

A representative random sample of 510 Málaga citizens was drawn following a stratified sampling procedure on public census data. The sample was stratified into three segments belonging to urban, metropolitan and rural municipalities. The questionnaire was administered face to face in December 2009 in 24 locations in the province to the population over 18 years old. The sampling quotas were proportional to the population of each location in terms of gender and age class. Table 2 summarizes the socioeconomics of the surveyed population. These fit well to the Malaga population in terms of gender and age (IEA, 2009). The $\chi 2$-tests failed to reject the representativeness of the sample.

[Table 2 around here]

Málaga is a coastal province of Andalucía with more than 77% of its area having mountainous landscapes with typical Mediterranean vegetation and a significant diversity of

[1] A translated version of the questionnaire including the information provided to the respondents can be obtained from the authors upon request.

ecosystems. The regional fire management plan currently includes controlled grazing as a management tool to complement the widespread use of heavy machinery and substituting where appropriate the traditional linear unshaded fuel breaks to reduce costs and negative landscape impacts.

3.2 Econometric models

Discrete choice experiments are based on the random utility model (McFadden, 1974) and Lancaster's theory (Lancaster, 1966; Train, 2009), and ask respondents to make trade-offs between different programs characterized by a set of attributes and levels. It is assuming that the individuals will choose the alternative providing them with the highest utility. In the following we will discuss the models' ability to model heterogeneity. The econometric specifications are intensively written in the literature, and will therefore not be repeated here. We refer to Louviere et al. (2000), Haab and McConnell (2002), Train (2003), Vermunt and Magidson (2005), Campbell et al. (2014) for specifications and applications.

Taste heterogeneity can be explored through the use of socioeconomic characteristics or attitudinal variables (i.e. observed heterogeneity). However, it may not always be possible to explain taste heterogeneity related to observed variables due to the inherent randomness in choice behaviour (Hess 2007). Several modelling approaches are able to model this unobserved heterogeneity with either continuous distributions, discrete distributions or a mixture of both (Boeri et al. 2011).

The continuous representation of preference in the random parameter logit (RPL) model introduces taste variation by assuming that each member in the sample has a different set of utility parameters. The RPL model controls for heterogeneity, assuming that each individual in the sample has a different set of utility parameters and, therefore, assessing the distributional impacts across individuals. Furthermore, RPL specifications can allow for correlations across random parameters when the likelihood of correlation in preferences for the different attributes may be significant (see e.g. Campbell et al., 2014; Hanley et al., 2010; Hynes et al., 2008). RPL models fit best when individuals' preferences distribute continuously and can be described by continuous distribution functions like the normal distribution.

In contrast, latent class (LC) models offer an alternative perspective to the RPL, replacing the continuous distribution with a discrete distribution (Green and Hensher, 2010). This approach is suitable when preference variation can be explained in the form of clusters, i.e. taste intensities take place over a finite number of classes of individuals rather than over continuous value distributions. LC models impose more structure on the choice model but in return allow for descriptions of segment heterogeneity in the data. Latent class approaches make use of two sub-models, one for class allocation, and one for within class choice (Hess 2007). The former models the probability of an individual being assigned to a specific class as a function of attributes of the respondent and possibly of the alternatives in the choice set. The within class model is then used to compute the class-specific choice probabilities for the different alternatives, conditional on the tastes within that class (Hess 2007). LC models presented an initial caveat due to the underlying assumption of within group homogeneity. Undoubtedly, it is improbable to expect that all individuals with identical socioeconomic characteristics will have the same preferences (Bujosa et al. 2010). Therefore, a natural extension of the fixed parameter latent class model is a random parameter class model which allows for another layer of preference heterogeneity within a class (Greene and Hensher 2010). The LC model in this study simultaneously classifies respondents in a number of classes depending on a number of covariates and estimates utility parameters based on random parameter model procedure, allowing for a common random effect for all the classes and a specific random component for each class (Justes et al., 2014; Soliño and Farizo, 2014).

Several authors have compared the performance of RPL and LC approaches to choice data to determine which one fits the data better and to examine differences in welfare estimates (Birol et al., 2006; Boeri et al., 2011; Boxall and Adamowicz, 2002; Broch and Vedel, 2012; Bujosa et al., 2010; Colombo et al., 2011; Greene and Hensher, 2003; Holmes et al., 2012; Hynes et al., 2008; Kosenius, 2010; Provencher and Bishop, 2004; Shen, 2009). The empirical results show there is no clear pattern indicating which approach is superior and the issue of which model provides the best description of the data is likely to be data dependent (Boeri et al., 2011). Bujosa et al. (2010), Hensher and Greene (2010) and Yoo and Ready (2014) favour the use of latent class random parameter models, since they found that this model delivered the best overall fit.

The discrete mixture (DM) model is a special case of a latent class model. It exploits the class membership concept in the context of random coefficients models (Hess 2007). Like LC models, DM models allow the relaxation of the assumption that a given taste parameter has the same distribution for all the respondents. DM models are RPL models where a mixture of distributions can be allowed for specific attributes hypothesized to hold significantly different preferences among the respondents. Allowing a mixture of two distributions, may unveil relevant aspects that could not be ascertained with a unique random parameter distribution. Thus, DM models may be seen as a mix of the LC and the RPL model, where classes are specified for specific parameters, and the other parameters are assumed to have a joint distribution (Campbell et al., 2013).

DM models have been more sparingly used compared to RPL and LC models, although they seem to be suited for unveiling contrasting taste preferences among the population for determined attributes. Hess et al. (2007) test DM models in transportation finding better performance for these models than their continuous RPL counterparts. Doherty et al. (2013) recommend DM models when the analyst wishes to constrain all cost heterogeneity to the negative preference domain. Campbell et al. (2014) use DM models to tease out heterogeneity in recreational forest access in Denmark. DM models allow the unveiling of preference groups with opposite preferences that otherwise are not shown by RPL models.

In this study we make use of the aforementioned modelling approaches to model unobserved heterogeneity in three different ways- by a random logit model, RPL (Train, 2009), a random latent class model, LC (Vermunt and Magidson, 2005) and a discrete mixture model, DM (Campbell et al., 2014; Doherty et al., 2013). The RPL and LC models incorporate socioeconomic and attitudinal variables assessing the observed heterogeneity and its influence in the preference for moving out of the status quo scenario and in explaining the segment allocation respectively. We extend the LC model to allow for heterogeneity both within and across groups, allowing for variation of the parameter vector within classes as well as between classes. Finally and following Hess (2007) and Campbell et al. (2014), the DM model explores the class allocation probabilities independently of explanatory variables. These approaches may provide complementary views on preferences allowing a better understanding of the distribution of a given attribute and its linkage with preferences when distributed across the segments of LC.

4. Results

4.1 Perceptions on forest fires: importance and causality

The valuation questionnaire contained two introductory questions aimed at testing the respondents' perception of forest fires. The first question asked respondents to choose from a list the two most important environmental problems in Andalucía. Forest fires were considered either the first or the second most important environmental problem by 37% of the sample. The second question asked respondents to choose according to their opinion the most worrying cause of forest fires from a list of five causes. Arson (i.e. the criminal act of deliberately setting fire to property) and land use change purposes are frequently reported in the media and were also raised by the respondents in the focus groups. Agricultural and pastoral burning are, according to fire statistics and research, the most important causes of forest fires in Andalucía (Priego González de Canales and Lafuente, 2007). 56% of the respondents chose arson as the most worrying cause of forest fires. Land use change was chosen by almost 30% of the sample. In contrast, pastoral and agricultural burning together accounted for less than 15% of the responses. These results are in accordance with other studies (De Castro et al., 2007) and show that the awareness the population have regarding forest fires is not coupled with a good knowledge on the underpinning causes. Consequently there exists a large disparity between fire statistics and citizens' perception. We used the responses to these two questions as covariates and class membership variables in the RPL and LC models, respectively, to test their explanatory potential as sources of observed heterogeneity.

4.2 RPL, LC and DM results

Out of the total 510 respondents we removed 101 protest responses and 12 inconsistent choices, leading to a final sample of 397 individuals of which 97 were genuine zeros bidders. No clear pattern or socioeconomic feature was found to characterize protesters.

The ASC was dummy coded taking the value of 1 if the individual chose the status quo option and 0 elsewhere. The three fire-related attributes, fuel break cleaning technique (CL_BB, CL_CG, CL_PB), fuel break design (DG_LINS, DG_IRRU, DG_IRRS) and density of fuel breaks (DE_MED DE_HIGH; DE_VHIGH), were effects coded to avoid correlation with the ASC (Bech and Gyrd-Hansen, 2005). The status quo level was scarification with angle dozer, linear unshaded fuel breaks and low density of fuel breaks respectively and corresponded to the reference level.

Covariates such as education, income or recreational habits usual in stated preference studies were also considered here, together with other socioeconomics that from the focus groups' experience we hypothesized could be relevant, such as employment status or town of residence size. These together with the previous two attitudinal variables amount the seven covariates tested in the RPL and LC models (Table 3).

As the fire-related attributes in the model have been effects-coded, it is also worth noting that for each attribute the magnitude of the omitted 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). Following Dominguez-Torreiro and Soliño (2011), an additional column representing the adjusted marginal utility gains from the base level situation for each of the levels of the effects-coded fire-related attributes has been included in tables 4,6 and 7 to make clearer the interpretation of the results.

4.2.1 RPL results

Table 4 shows the results of the first model estimated, an RPL model with panel structure, 500 Halton draws and allowing for correlation among the random parameters. All the management attributes were modelled as random parameters according to a normal distribution. Cost attribute and the ASC remained constant. The model was estimated with NLOGIT 4.0 software (Greene, 2007). Observing the values for the adjusted coefficients, the three cleaning tools (CL_BB, CL_CG, CL_PB) are significant, retrieving similar and negative values for light machinery (CL_BB) and controlled grazing (CL_CG), while prescribed burning (CL_PB) holds the most negative value among the three cleaning tools. Moving to the design-related attribute levels (DG_LINS; DG_IRRU, DG_IRS), only the linear shaded designs (DG_LINS) retrieve significant and negative values, indicating a preference for the traditional linear unshaded designs (DG_LINU). The remaining design fire-related attribute levels are non-significant, suggesting that the design of preventive structures plays a minor role in shaping social preferences. When it comes to the density of fuel breaks (DE_MED; DE_HIGH; DE_VHIGH) (that is coupled with a decrease in the burnt area), medium (DE_MED) and very high density levels (DE_VHIGH) retrieve significant values, negative and positive, respectively, while the high density level (DE_HIGH) remains non-significant.

The cost attribute shows a negative value as expected, while the negative value of the ASC indicates that *ceteris paribus* respondents experience a disutility from the SQ situation and would be willing to move to any of the proposed alternatives. Despite extensive testing of interactions between random parameters and the covariates we hypothesized could contribute to explain systematic taste variation, no significant outcome was provided. When new policy designs are investigated it is of interest to know which respondent characteristics increase the probability of agreeing with the "policy-on" options and which with the probability of the "policy-off" option (Colombo et al., 2009). The interaction of some of these covariates (Table 2) with the ASC retrieved significant results that contribute to explain respondents' willingness to move from the SQ situation to alternative scenarios.

[Table 4 around here]

The working status (WORK) and the practice of forest recreational activities (RECRE) play a significant role in deciding whether people are willing to move to alternative management scenarios. While unemployed people are more likely to stay in the current situation, recreationists are willing to move to management options.

The standard deviations are statistically significant for all parameters and very large, indicating a large heterogeneity in the respondents' preferences. Because we allowed for correlated parameters, the reported standard deviations are not independent. Inspecting the diagonal values in the Cholesky matrix (Table 5), some patterns could be identified in terms of the level of variance directly attributable to the parameters themselves. The variance of the cleaning attribute levels is significant and most of it attributable to the parameters themselves. In contrast, the variance of the design and density fire-related attributes is either not statistically significant or a noteworthy part of it is attributable to the interactions with other parameters.

[Table 5 around here]

Results concerning the density of fuel breaks attribute levels were counterfactual when confronted with our hypothesis built on the focus group sessions. Most people in these groups were pleased to increase the density of fuel breaks to a certain extent. However, when changes towards high and very high densities of fuel breaks were proposed, we observed two very distinct groups among the participants. Some of them were concerned with decreasing the burnt area and therefore supported high increases in density. Some others in contrast, stated that it could bring some negative trade-offs in terms of landscape impact and hence showed reluctance for these increases. Looking at Table 5 we observe a large standard deviation for fuel break attribute, probably reflecting this.

4.2.2 Discrete mixture results

To explore whether the polarization in the preference for fuel breaks observed in the focus groups could also be present in our sample, two discrete mixture models were estimated, where a mixture of Normals was applied to the highest (DE_VHIGH) and second highest (DE_HIGH) levels of fuel break densities, respectively (Table 6).

Those models were estimated using Biogeme software (Bierlaire, 2003). Observing the adjusted coefficients, DE_HIGH retrieves significant and negative values for its two distributions, with 34% of the sample showing very negative mean values for the parameter, indicating that an important disutility is experienced for the DE_HIGH parameter, even if it is a small share of the population that experiences it. DE_VHIGH attribute levels show both positive and negative mean values, with 54% of the respondents attached to the latter. We note that the negative values are numerically much higher than the positive ones for the DE_VHIGH parameter. These models detected that some people hold very negative preferences for increases in the density of fuel breaks. Preferences of risk avoiders could be ascribed to the positive mean distributions while landscape-aware profiles would be allocated into the negative mean distributions of the parameters. Finally, allowing for mixed distributions for the density levels also had an impact on the estimates of other coefficients, especially for light machinery (CL_BB), which shows results more according to our expectations resulting from the focus group sessions. This may be caused by the RPL model allowing for correlated parameters, and if the parameters for fuel break density do not capture the heterogeneity of the population they will carry over to the other variables too.

[Table 6 around here]

4.2.3 LC results

The outcomes of the focus groups suggested that different groups of respondents may exist with distinctive trade-off attitudes between fire prevention and other aspects of landscape management. This was further supported by the large heterogeneity observed in the RPL model for the management attribute levels together with the outcomes of the discrete mixture models. Applying an LC model was the logical next step. The LC model was estimated with Latent Gold 4.5 software (Vermut and Magdison, 2005). The Akaike Information Criterion (AIC) is used to determine the number of model classes. The LC model that provided the best equilibrium between the information criteria and the degree of explicability of results according to our hypothesis was a four-class model shown in Table 7. We assume that fire-related attributes behave randomly in two ways: a common random effect for all the classes and a specific random component for each class. This specification allows us to isolate the common and the specific random components for each attribute and each class, improving the accuracy of the model.

[Table 7 around here]

The class size for the LC model shows that more than one third of the respondents could be allocated to the first class. The second and third classes are about of equal size, with 25% of the respondents distributed to each of them while the remainder of the sample (17.6%) fits into the fourth class.

Respondents in class 1 show positive and significant values for all the fire related attributes. The levels of the design attribute show the lowest values in preferences while the levels of the density attribute and the levels of the cleaning tool attribute account for the higher values. More specifically, medium and high densities of fuel break achieve the highest values in taste parameters. Class 1 was named *typical* as these results coincide very closely with the work of Castro et al. (2007) on the social perception of forest fires in Andalucía. They also correspond with the most frequent pattern observed among the participants in the focus groups and in the pilot tests: people were mainly concerned with the decrease in burnt area that the increase in density may bring about and with some changes in the fuel break cleaning practices, while design issues played a minor role in shaping their preferences. The respondents considering forests fires as one of the most important problems in Andalucía, are most likely to belong to this class, while urban highly educated people and these with outdoor recreational habits are less likely to be addressed to this group.

Class 2 shows similarities with Class 1 in terms of the relative importance of the taste parameters within the class: density fire-related attributes show the highest values, followed by cleaning techniques. The distinctive feature of this group is their relatively low sensitiveness to the cost attribute. This leads us to conclude that respondents in this class did not consider their budget restrictions and accordingly we named it the *yea-saying* class. Yea-saying behaviour was also found by Holmes et al. (2012) among respondents evaluating wildfire protection programmes. In their case, responses from individuals less likely to have personal experience of the effects of wildfire reflected a way of simplifying decisions, ignoring some fire-related attributes (cost among them) while expressing support for wildfire protection programs. We hypothesized that topics such as forest fires that have a high social relevance, are more prone to subordinate economic preferences in favour of expressive motivations. Unemployed respondents in the sample are less likely to belong to this class, probably because their budget constraints are less likely to lead them to yea-saying behaviour.

Class 3 is tagged the *burnt-worried* class. It retrieves distinctively high values for the fire-related attributes describing increases in the fuel breaks' density. Respondents seem to mainly shape their preferences according to the decrease in burnt area and not so much to the way the increase and maintenance of the prevention structures is achieved. In contrast to the previous classes, none of the class membership variables estimated in the model show any explicative power.

Finally, Class 4 is the most dissimilar when compared with the other three classes, showing negative values for all the levels of the fire-related attributes, being tagged as the *against* class. The respondents experience a significant disutility when moving from the SQ scenario. Because protest responses were previously removed, we hypothesize that disutility has a different origin. Respondents in this class neither refused to participate in the hypothetical market nor showed distrust in the administration (as most of the protesters did). The work variable plays the biggest role in determining class membership, with unemployed people having a higher probability of belonging to this class. On the contrary, people considering forest fires as a very relevant environmental problem, and also those considering arson and land use change as the main drivers of forest fires, are less likely to be allocated to this group.

4.2.4 Marginal WTP results

Individuals' coefficients for the fire related attributes are converted into marginal willingness to pay (mWTP) following the Lusk et al. (2003) formula for effect-coded attributes and applying the Krinsky and Robb (1986) procedure with 1,000 replications for the mean and 95% confidence intervals. The estimates for the RPL, DM models and LC models are reported in Tables 8 and 9 and in Figures 2-5[2].: The mean negative values in RPL are disentangled in LC estimates, where the *against* class shows distinctively negative values while the *yea-saying* class expresses rather high WTP values when compared with the other classes. We notice that this leads to a higher overall WTP in the LC model than for the RPL model for all the estimates. However, the LC model allows to identify the source of these high WTP estimates in the yea-saying class. The DM models shed light on the preferences for the density attribute levels showing that negative mean WTP estimates are obtained for the high densities. This is more in line with what was observed in the focus groups in relation to the role of the design attributes.

[Insert Figures 2-4 around here]

5. Concluding discussion

Forest fire is a large problem in the Mediterranean area and receives a lot of media attention. This causes people to have strong feelings on the issue, yet often on an uninformed basis. Consequently, resource use on fire prevention and suppression is affected by not only efficiency and effectiveness, but also public acceptance. Various factors influence this, such

[2] Because all the attributes were effects-coded, WTP estimates are calculated taking into account the estimates for the baseline variables SWA, LINU and LOW (Domínguez-Torreiro and Soliño 2011; Lusk et al. 2003).

as the size of the damage and where it occurs in relation to where people live, the trade-offs with the aesthetic view on the landscape, the relation to what traditional landscape management is and the knowledge the individual has. These cause that a large heterogeneity to be expected. Consequently this study investigates heterogeneity in the general public's preferences for fire prevention in the Mediterranean. Apart from that, the study contributes to the literature with empirical investigation of the use of different ways of modelling heterogeneity. The three different models estimated provide different aspects of the heterogeneity of preferences for fire prevention, showing that using a combined approach of continuous and discrete distributions is appropriate for eliciting preference heterogeneity when dealing with extreme preference patterns either at the attribute or at the population level.

5.1 Preferences for fire prevention and management implications

Overall we find that that people are not indifferent as to how fire prevention is carried out. On average we observe a negative marginal WTP for prescribed burning instead of the classic scarification with angledozer and also that linear unshaded fuel break designs are preferred over shaded and irregular designs. Policy makers are reluctant to apply prescribed burning due to expected rejection by the population (Xanthopoulos et al. 2006) as also our RPL model shows. However, the LC model shows that rejection is not general, with more than half of the population in favour of the use of this management tool. Similarly, this model shows that softer fuel break cleaning techniques like backpack brush-cutters and controlled grazing are also preferred over the classic techniques by most of the population. This supports the ongoing initiatives employing controlled grazing as a complementary tool for fuel management (Ruiz-Mirazo et al., 2011). This share of the population that seem to be these opposed to changes in the current management of prevention structures, we identify them as more likely being unemployed, not recreating in nature much, and less likely seeing forest fires as the main environmental problem or caused by the main reasons argued in the media. On this basis it is difficult to affirm that it is a specific group of people who can be targeted in policy making. Rather it calls for further analyses of what causes the opposition of prescribed burning.

Looking at the size of the marginal WTP we see that the fuel break design attribute contributes to a lower extent to the WTP of the respondents when compared to the other management attributes. This aspect contrasts with the technical/research debates where it is a major issue (Agee et al., 2000; Duguy et al., 2007; Husari et al., 2006; Reinhardt et al., 2008; Schmidt et al., 2008). Thus, results provide evidence that a relevant gap may exist between forest managers and society in terms of fire perception.

The density of fuel breaks holds a trade-off between reducing risk (a high density) and the landscape aesthetics. The results of the valuation study for this non-market trade-off reveal taste heterogeneity among the population, showing that even within the most worried group the highest density is not necessarily preferred. Our results also show that people more concerned about forest fires are not necessarily those that are more informed about the causes, highlighting the fact that the strategies for fire communication in Spain need improving.

Finally, some uncertainties still remain about how to relate those findings to the articulation of fire prevention policies and communication strategies. Advocating for changes in fire prevention needs committed politicians able to set up long-term plans to reduce biomass content at a landscape level and increased work on the human causes of forest fires. Change in the traditional fire prevention structures is one of the measures within a broader view of fire prevention measures. Therefore future research direction should aim to explore to what extent citizens will support these changes.

Finally, the estimates provided by the different models show some disparities that can have a significant impact if these were intended to be used in policy making processes. The findings support the prospective approach employed and signal the direction of future research. Despite forest fires constituting a topic of high concern among the population, fire prevention is not perceived homogeneously by all the citizens. If prevention policies aim to increase the welfare of the citizens and gain their support, specific solutions may need to be devised instead of one-serves-all policies that have been much more the case until nowadays.

5.2 Comparison of heterogeneity models

The RPL model is useful for allowing some taste heterogeneity, getting an average estimate of the population preferences. In the current application however, preferences were so heterogeneous that they could not easily be described with the chosen normal distribution. Other continuous distributions could have been used (and were in fact tried), but we found that discrete distributions may better allow for describing the heterogeneity.

The important contribution of the LC model compared to the RPL approach is to better capture the variation in preferences for specific segments of the population. This segmentation let us characterize two extreme classes among the respondents whose preferences have important implications in the mean welfare estimates, i.e. the *yea-saying* class and the *against* class, that otherwise are not captured in the RPL model. This is important as we would rather not to kick respondents out of the sample; but instead identify the implication of the potential bias they may give (the yea-saying group). In the LC model used here we estimated a standard deviation for each attribute within each class, that resembles advanced RPL distributions although allowing for more flexibility than in the typical LC models (e.g. Jacobsen et al., 2012). Furthermore, we included a common standard deviation for all attributes across all classes. This is done to make classes more meaningful with respect to the effect of attributes (Farizo et al., 2014; Vermont and Magidson, 2005)

Some extreme patterns in taste variation for the fuel break density attribute couldn't be disentangled either by a single continuous distribution approach (RPL) or by class segmentation (LC). For this purpose, the DM model resulted particularly helpful in revealing heterogeneity at the attribute level for an attribute that has significant budgetary and landscape implications in the planning of strategies for fire prevention. Consequently we find the DM useful if we have applications with a particular attribute of interest where we may observe opposing opinions.

Overall, the LC model might better capture our intuition about some of the respondents based on our observations in the focus groups (i.e. burnt-worried class) and on evidences from the literature (i.e. yea saying class as in Homes et al.,2012). Although it is not possible to choose between the different models based on goodness of fit, as each of them provides with different pictures of preferences and WTP (Yoo and Ready, 2014), our results are in line with previous work favouring the latent class models (Bujosa et al.,2010; Hensher and Greene, 2010; Yoo and Ready,2014). This is likely a result of the valued good being rather unfamiliar in implementation yet familiar in consequences. Still we would like to emphasize the role of the other models to better capture different components of the heterogeneity. In the current study we can see that the RPL model is good at unveiling the share of the population not willing to move from the SQ scenario, which overall has a higher influence in the mean WTP estimates than other segments of the population. Finally, DM models show reflect the impact of considering extreme preference patterns for the density attribute, by retrieving mean weighted WTP values for the attribute that reflect the very negative preferences held by a share of the population.

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7. References

Absher, J.D., Vaske, J.J., Shelby, L.B., 2009. Residents' Responses to Wildland Fire Programs: A Review of Cognitive and Behavioral Studies. USDA Forest Service, Pacific Southwest Research Station, Albany, CA, 31 pp.

Agee, J.K., Bahro, B., Finney, M.A., Omi, P.N., Sapsis, D.B., Skinner, C.N., van Wagtendonk, J.W., Phillip Weatherspoon, C., 2000. The use of shaded fuelbreaks in landscape fire management. Forest Ecology and Management 127, 55-66.

Barrio, M., Loureiro, Chas, M.L., 2007. Aproximación a las pérdidas causadas por los incendios forestales en Galicia en 2006. Economía Agraria y Recursos Naturales 14(7), 45-64.

Bech, M., Gyrd-Hansen, D., 2005. Effects coding in discrete choice experiments. Health Economics 14, 1079-1083.

Bierlaire, M., 2003. BIOGEME: A free package for the estimation of discrete choice models. Proceedings of the 3rd Swiss Transportation Research Conference, Ascona, Switzerland

Birol, E., Karousak.is, K., Koundouri, P., 2006. Using a choice experiment to account for preference heterogeneity in wetland attributes: The case of Cheimaditida wetland in Greece. Ecological Economics 60, 145-156.

Boeri, M., Doherty, E., Campbell, D., Longo, A., 2011. Accommodating for taste and variance heterogeneity in discrete choice, Second International Choice Modelling Conference, Leeds, UK.

Boxall, P., Adamowicz, W., 2002. Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach. Environmental and Resource Economics 23, 421-446.

Broch, S.W., Vedel, S.E., 2012. Using choice experiments to investigate the policy relevance of heterogeneity in farmer agri-environmental contract preferences. Environmental and Resource Economics 51, 561-581.

Bujosa, A., Riera, A., Hicks, R.L., 2010. Combining Discrete and Continuous Representations of Preference Heterogeneity: A Latent Class Approach. Environmental and Resource Economics 47, 477-493.

Calkin, D.E., Venn, T., Wibbenmeyer, M., Thompson, M.P., 2012. Estimating US federal wildland fire managers' preferences toward competing strategic suppression objectives. International Journal of Wildland Fire 22, 212-222.

Campbell, D., Vedel, S.E., Thorsen, B.J., Jacobsen, J.B., 2014. Heterogeneity in the WTP for recreational access: distributional aspects. Journal of Environmental Planning and Management, http://www.tandfonline.com/doi/full/10.1080/09640568.2013.793173

Caparrós, A., Oviedo, J. L., Campos, P., 2008. Would you choose your preferred option? Comparing choice and recoded ranking experiments. American Journal of Agricultural Economics 90(3), 843-855.

Choi, A.S., Fielding, K.S. 2013. Environmental attitudes as WTP predictors: A case study involving endangered species. Ecological Economics 89, 24-32.

Colombo, S., Hanley, N., Louviere, J., 2009. Modeling preference heterogeneity in stated choice data: an analysis for public goods generated by agriculture. Agricultural Economics 40, 307-322.

Colombo, S., Hanley, N., Torres, C., 2011. Incorrectly accounting for taste heterogeneity in choice experiments: Does it really matter for welfare measurement? University of Stirling, Division of Economics, Stirling.

De Castro, R., Simarro, M.E., Priego, C., Lafuente, R., Sancho, A., 2007. Investigación social sobre los incendios forestales en Andalucía, Wildfire 2007. 4th International Wildland Fire Conference, Sevilla.

Doherty, E., Campbell, D., Hynes, S., 2013. Models of Site-choice for Walks in Rural Ireland: Explorin Cost Heterogeneity. Journal of Agricultural Economics 64, 446-466.

Domínguez-Torreiro, M,, Soliño, M., 2011. Provided and perceived status quo in choice experiments: Implications for valuing the outputs of multifunctional rural areas. Ecological Economics 70, 2523-2531.

Duguy, B., Alloza, J.A., Röder, A., Vallejo, R., Pastor, F., 2007. Modelling the effects of landscape fuel treatments on fire growth and behaviour in a Mediterranean landscape (eastern Spain). International Journal of Wildland Fire 16, 619-632.

FAO, 2013. The State of Mediterranean Forests. Available at: http://www.fao.org/docrep/017/i3226e/i3226e.pdf

Farizo, B., Joyce, J., Soliño, M., 2014. Dealing with heterogeneous preferences using multilevel mixed models. Land Economics 91, 181-198.

González-Cabán, A., Loomis, J.B., Rodriguez, A., Hesseln, H., 2007. A comparison of CVM survey response rates, protests and willingness-to-pay of Native Americans and general population for fuels reduction policies. Journal of Forest Economics 13, 49-71.

González-Cabán, A., Wohlgemuth, P., Loomis, J.B., 2004. Costs and benefits of reducing sediment production from wildfires through prescribed burning: The Kinneloa fire case study, II Simposio Internacional sobre Políticas, Planificación y Economía de los Programas de Protección Contra Incendios Forestales, Córdoba (España).

Green, L.R., 1977. Fuelbreaks and other fuel modification for wildland fire control. USDA Agr. Hdbk.

Greene, W.H., Hensher, D.A., 2003. Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. Applied Economics 45, 1897-1902.

Greene W.H., 2007. NLogit Version 4.0, Econometric Software. New York and Sidney.

Haab, T.C., McConnell, K.E., 2002. Valuing environmental and natural resources: the econometrics of non-market valuation. Edward Elgar Publishing, Cheltenham.

Hanley, N., Czajkowski, M., Hanley-Nickolls, R., Redpath, S. 2010. Economic values of species management options in human-wildlife conflicts: Hen Harriers in Scotland. Ecological Economics 70, 107-113.

Hensher, D.A., Rose, J.M., Greene, W.H., 2007. Applied choice analysis. A primer. Cambridge University Press. Cambridge.

Hess, S., Bierlaire, M., Polak, J.W., 2005. Capturing Correlation and Taste Heterogeneity with Mixed GEV Models, in: Scarpa, R., Alberini, A. (Eds.), Applications of Simulation Methods in Environmental and Resource Economics. Springer Netherlands, Doordrecht, pp. 55-75.

Hesseln, H., Loomis, J.B., González-Cabán, A., 2004. Comparing the economic effects of fire on hiking demand in Montana and Colorado. Journal of Forest Economics 10, 21-35.

Holmes, T.P., González-Cabán, A., Loomis, J., Sánchez, J., 2012. The effects of personal experience on choice-based preferences for wildfire protection programs. International Journal of Wildland Fire 22, 234-245.

Husari, S., Nichols, T., Sugihara, N.G., Stephens, S.L., 2006. Fire and Fuel Management, in: Sugihara, N.G., Van Wagtendonk, J.W., Shaffer, K.E., Fites-Kaufman, J., Thode, A.E. (Eds.), Fire in California's ecosystem. University of California, Berkeley and Los Angeles, pp. 444-465.

Hynes, S., Hanley, N., Scarpa, R., 2008. Effects on welfare measures of alternative means of accounting for preference heterogeneity in recreational demand models. American Journal of Agricultural Economics 90, 1011-1027.

IESA/CSIC, 2007. Ecobarómetro de Andalucía.

Jacobsen, J.B., Lundhede, T.H., Thorsen, B.J., 2012. Valuation of increasing wildlife populations above survival. Biodiversity and Conservation 543-563

Jensen, C., Panduro, T., Lundhede, T.H., 2014. The Vindication of Don Quijote: The impact of noise and visual pollution from wind turbines. Land Economics. In press

Justes, A., Barberán, R., Farizo, B.A., 2014. Economic valuation of domestic water uses. Sicience of the total environment 472, 712-718.

Kanninen, B., J., (Ed.), 2007. Valuing environmental amenities using states choice studies. Springer Netherlands, Doordrecht

Kaval, P., Loomis, J., Seidl, A., 2007. Willingness-to-pay for prescribed fire in the Colorado (USA) wildland urban interface. Forest Policy and Economics 9, 928-937.

Kosenius, A.-K., 2010. Heterogeneous preferences for water quality attributes: The Case of eutrophication in the Gulf of Finland, the Baltic Sea. Ecological Economics 69, 528-538.

Lancaster, K.J., 1966. A new approach to consumer theory. Journal of Political Economy 74, 132-157.

Loepfe, L., Martínez-Vilalta, J., Oliveres, J., Piñol, J., Lloret, F., 2010. Feedbacks between fuel reduction and landscape homogenisation determine fire regimes in three Mediterranean areas. Forest Ecology and Management 259, 2366-2374.

Loomis, J., González-Cabán, A., 1994. Estimating the value of reducing fire hazards to old-growth forests in the pacific-northwest - a contingent valuation approach. International Journal of Wildland Fire 4, 209-216.

Loomis, J., González-Cabán, A., 2008. Contingent valuation of fuel hazard reduction treatments, in: Holmes, T.P., Prestemon, J.P., Abt, K.L. (Eds.), The Economics of Forest Disturbances: Wildfires, Storms and Invasive Species. Springer, pp. 229-243.

Loomis, J., Gonzalez-Caban, A., Hesseln, H., 2004. Multicultural Evaluation of the Performance of Contingent Valuation for Forest Fire Prevention. Contemporary Economic Policy 22, 407-419.

Loomis, J.B., González-Cabán, A., 1998. A willingness-to-pay function for protecting acres of spotted owl habitat from fire. Ecological Economics 25, 315-322.

Loomis, J.B., Trong Hung, L., González-Caban, A., 2005. Testing transferability of willingness to pay for forest fire prevention among three states of California, Florida and Montana. Journal of Forest Economics 11, 125-140.

Loomis, J.B., Trong Hung, L., González-Cabán, A., 2009. Willingness to pay function for two fuel treatments to reduce wildfire acreage burned: A scope test and comparison of White and Hispanic households. Forest Policy and Economics 11, 155-160.

Louviere, J. L., Hensher, D.A., Swait, J.D. 2000. Stated choice methods. Analysis and application. Cambridge University Press, Cambridge.

Lundhede, T.H., Jacobsen, J.B., Hanley, N., Strange, N., Thorsen, B.J. 2014. Incorporating Outcome Uncertainty and Prior Outcome Beliefs in Stated Preferences. Land Economics, In Press

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. American Journal of Agricultural Economics 85, 16-29.

Martínez, J., Vega-Garcia, C., Chuvieco, E., 2009. Human-caused wildfire risk rating for prevention planning in Spain. Journal of Environmental Management 90, 1241-1252.

Martinson, E.J., Omi, P.N., 2003. Performance of Fuel Treatments Subjected to Wildfires, USDA Forest Service proceedings RMRS-P-29, pp. 7-14.

Mavsar, R., Japelj, A., Kovac, M., 2013. Trade-offs between fire prevention and provision of ecosystem services in Slovenia. Forest Policy and Economics 29, 62-69.

McCaffrey, S., Toman, E., Stidham, M., Shindler, B., 2012. Social science research related to wildfire management: an overview of recent findings and future research needs. International Journal of Wildland Fire 22, 15-24.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior, in: Zarembka, I. (Ed.), Frontiers in econometrics. Academic Press, New York, pp. 105-142.

Ministry of Environment, 1998. Spanish Strategy for the Conservation and Sustainable Use of Biodiversity. Environment Secretariat, Madrid.

Montiel, C., San-Miguel, J., 2009. Policy analysis reveals the need for new approaches, in: Birot, Y (Ed.), Living with wildfires: what science can tell us. EFI Discussion Paper 15. European Forest Institute, Joensuu, pp. 63-67.

Moreira, F., Viedma, O., Arianoutsou, M., Curt, T., Koutsias, N., Rigolot, E., Barbati, A., Corona, P., Vaz, P., Xanthopoulos, G., Mouillot, F., Bilgili, E., 2011. Landscape – wildfire interactions in southern Europe: Implications for landscape management. Journal of Environmental Management 92, 2389-2402.

Morey, E., Thacher, J., Breffle, W., 2006. Using angler characteristics and attitudinal data to identify environmental preference classes: a latent-class model. Environmental and Resource Economics 34, 91-115.

Morriondo, M., Good, P., Durao, R., Bindi, M., Giannakopoulos, C., Corte-Real, J., 2006. Potential impact of climate change on fire risk in the Mediterranean area. Cliamte Research 31, 85-95.

Mouillot, f., Rambal, S., Joffre, R., 2002. Simulating climate change impacts on fire frequency and vegetation dynamics in a Mediterranean-type-ecosystem. Global Change Biology 8, 423-437.

Muys, B., 2013. Sustainable development within planetary boundaries: a functional revision of the definition based on the thermodynamics of complex social-ecological systems. Challenges in Sustainability 1, 41-52.

Pausas, J.G., 2004. Changes in Fire and Climate in the Eastern Iberian Peninsula (Mediterranean Basin). Climatic Change 63, 337-350.

Pausas, J.G., Llovet, J., Rodrigo, A., Vallejo, R., 2008. Are wildfires a disaster in the Mediterranean basin? - A review. International Journal of Wildland Fire 17, 713-723.

Piñol, J., Castellnou, M., Beven, K.J., 2007. Conditioning uncertainty in ecological models: Assessing the impact of fire management strategies. Ecological Modelling 207, 34-44.

Priego González de Canales, C., Lafuente, R., 2007. La investigación social como una nueva herramienta contra la lucha de los Incendios Forestales en Andalucía. IX Congreso Español de Sociología, Barcelona.

Provencher, B., Bishop, R.C., 2004. Does accounting for preference heterogeneity improve the forecasting of a random utility model? A case study. Journal of Environmental Economics and Management 48, 793-810.

Reiner, A.L., Vaillant, N.M., Fites-Kaufman, J., Dailey, S.N., 2009. Mastication and prescribed fire impacts on fuels in a 25-year old ponderosa pine plantation, southern Sierra Nevada. Forest Ecology and Management 258, 2365-2372.

Reinhardt, E.D., Keane, R.E., Calkin, D.E., Cohen, J.D., 2008. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. Forest Ecology and Management 256, 1997-2006.

Riera, P., Mogas, J., 2004. Evaluation of a risk reduction in forest fires in a Mediterranean region. Forest Policy and Economics 6, 521-528.

Riera, P., Peñuelas, J., Farreras, V., Estiarte, M., 2007. Valuation of climate-change effects on Mediterranean shrublands. Ecological Applications 17, 91- 100.

Ruiz-Mirazo, J., Robles, A.B., González-Rebollar, J.L., 2011. Two-year evaluation of fuelbreaks grazed by livestock in the wildfire prevention program in Andalusia (Spain). Agriculture, Ecosystems and Environment 141, 13-22.

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 Economics 81, 426-444.

Schmidt, D.A., Taylor, A.H., Skinner, C.N., 2008. The influence of fuels treatment and landscape arrangement on simulated fire behaviour, Southern Cascade range, California. Forest Ecology and Management 255, 3170-3184.

Soliño, M., 2010. External benefits of biomass-e in Spain: An economic valuation. Bioresource Technology 101, 1992-1997.

Soliño, M., Prada, A., Vázquez, M.X., 2010. Designing a forest-energy policy to reduce forest fires in Galicia (Spain): A contingent valuation application. Journal of Forest Economics 16, 217-233.

Soliño, M., Álvarez-Farizo, B., Vázquez, M.X., Prada A., 2012. Generating electricity with forest biomass: Consistency and payment timeframe effects in choice experiments. Energy Policy 41, 798-806.

Soliño, M., Farizo, B.A. 2014. Personal traits underlying environmental preferences: a discrete choice experiment. PLoS One 9(2): e89603. doi: 10.1371/journal.pone.0089603

Starbuck, C.M., Berrens, R.P., McKee, M., 2006. Simulating changes in forest recreation demand and associated economic impacts due to fire and fuels management activities. Forest Policy and Economics 8, 52-66.

Street, D.J., Burgess, L., 2007. The Construction of Optimal Stated Choice Experiments. Theory and Methods. Wiley: Hoboken, New Jersey.

Street, D.J., Burgess, L., Louviere, J.J., 2005. Quick and easy choice sets: Constructing optimal and nearly optimal stated choice experiments. International Journal of Research in Marketing 22, 459-470.

Toman, E., Shindler, B., 2006. Communicating the Wildland Fire Message: Influences on Knowledge and Attitude Change in Two Case Studies, in: Andrews, P.L., Butler, B.W. (Eds.), Fuels Management- How to Measure Success. Fort Collins, CO: USDA Forest Service, Rocky Mountain Research Station, Portland, OR, pp. 715-728.

Train, K., 2009. Discrete choice methods with simulation. Cambridge University Press. Cambridge, UK.

Valbuena-Carabaña, M., de Heredia, U.L., Fuentes-Utrilla, P., González-Doncel, I., Gil, L., 2010. Historical and recent changes in the Spanish forests: A socio-economic process. Review of Palaeobotany and Palynology 162, 492-506.

Varela, E., Giergicny, M., Riera, P., Mahieu, P., Soliño, M., 2014. Social preferences in fuel break management programmes in Spain: a choice modelling application to preventing forest fires. International Journal of Wildland Fire 23, 281-289.

Vaux, H.J., Gardner, P.D., Mills, T.J., 1984. Methods for assessing the impact of fire on forest recreation., Gen. Tech. Rep. PSW-79. Pacific Southwest Forest and Range Experiment Station, USDA Forest Service, Berkeley, CA, 19 pp.

Vélez Muñoz, R., 2000. Selvicultura preventiva, in: Vélez Muñoz, R. (Ed.), La defensa contra incendios forestales. McGraw-Hill, Aravaca (España), pp. 14.11-14.17.

Vélez Muñoz, R., 2004. Europa: desarrollo y fuego, II Simposio sobre Políticas, Planificación y Economía en la Defensa Contra Incendios Forestales, Córdoba (España).

Vermunt, J.K., Magidson, J., 2005. Technical guide for Latent GOLD 4.0: Basic and advanced. Belmont (Mass.): Statistical Innovations Inc.

Walker, S.H., Rideout, D.B., Loomis, J.B., Reich, R., 2007. Comparing the value of fuel treatment options in northern Colorado's urban and wildland-urban interface areas. Forest Policy and Economics 9, 694-703.

Westerberg V.H., Jacobsen, J.B. Lifran, R., 2013. The case for offshore wind farms, artificial reefs and sustainable tourism in the French Mediterranean. Tourism Management, 34, 172-183.

Winter, G., Vogt, C.A., McCaffrey, S., 2004. Examining social trust in fuel management strategies. Journal of Forestry, 8-15.

Winter, G.J., Fried, J.S., 2001. Estimating Contingent Values for Protection from Wildland Fire Using a Two-Stage Decision Framework. Forest Science 47, 349-360.

Xanthopoulos, G., Caballero, D., Galante, M., Alexandrian, D., Rigolot, E., Marzano, R., 2006. Forest Fuels Management in Europe, in: U.S. Department of Agriculture. Forest Service. Rocky Mountain Research Station (Ed.), Fuels Management- How to Measure Sucess: Conference Proceedings. Andrews, Patricia L.,Butler, Bret W.,(comps.), Portland, OR, pp. 29-46.

Tables and figures for "Understanding the heterogeneity of social preferences for fire prevention management"

Table 1. Fire-related attributes and levels

Fire-related Attributes	Levels
Fuel break cleaning technique (CL)	CL_SWA*:Scarification with angledozer
	CL_BB: Backpack brushcutter
	CL_CG: Controlled grazing
	CL_PB: Prescribed burning
Fuel break design (DG)	DG_LINU*: Linear unshaded
	DG _LINS: Linear shaded
	DG _IRRU: Irregular unshaded
	DG _IRRS: Irregular shaded
Density of fuel breaks (yearly burned area) (DE)	DE_LOW*: Low (1000 ha burnt)
	DE _MED: Medium (800 ha burnt)
	DE _HIGH: High (600 ha burnt)
	DE _VHIGH: Very High (400 ha burnt)
Annual payment	COST: €0*, €20, €60, €100, €140

*Status quo level.

Table 2. Socioeconomics of the surveyed respondents

Variable	Sample	Málaga population	Significance one-sample $\chi 2$-tests
Gender (% female)			
Female	261	625605	0.03
Male	249	599961	
Income (net disposable income per month)	1021.4 €	1326.4 €	
Age			0.882
18 – 39 years old	198	500371	
40 – 65 years old	175	420355	
65 or over years old	125	304840	
Municipality size			0.099
Metropolitan (> 100,000 inhabitants)	227	547605	
Urban (20,000 – 100,000 inhabitants)	180	425282	
Rural (< 20,000 inhabitants)	103	252679	

Table 3. Covariates/Class-membership variables in the RPL and LC Models

Variable	Description
EDU	Highest educational level (1: secondary education or higher; 0: otherwise)
WORK	Working situation (1: unemployed; 0: otherwise)
INCOME	Net monthly income (1: more than €1,200; 0: from €0 to €1,200)
TOWN	Size of town of residence (1: urban and metropolitan area; 0: rural area)
RECRE	Recreational visit to the countryside in the last year (1: yes; 0: no)
FIRE_MN	Forest fires as the 1st or 2nd most important environmental problem in Andalusia (1: yes; 0: no)
CAUSE	The most worrying cause of forest fires (1: arson and land use change purposes; 0: Stubble burning, pastoral burning and lightening)

Table 4. RPL with correlated parameters

Variables	RPL		
	Coef.	SDPD	Adj.[a]
Fire-related attributes			
CL_BB	0.232 (0.112)**	0.736(0.088)***	-0-190
CL_CG	0.221(0.105)**	0.786(0.074)***	-0.201
CL_PB	-0.875(0.119)***	1.013(0.107)***	-0.453
DG_LINS	-0.205(0.092)**	0.328(0.120)***	-0.630
DG_IRRU	-0.156(0.099)	0.407(0.125)***	-0.581
DG_IRRS	-0.064(0.110)	0.456(0.085)***	-0.489
DE_MED	-0.342(0.099)***	0.630(0.186)***	-0.307
DE_HIGH	0.141(0.110)	0.921(0.140)***	0.176
DE_VHIGH	0.236(0.126)*	1.080(0.164)***	0.271
ASC	-0.599(0.309)*	fixed	
COST	-0.029(0.000)***	fixed	
Covariates			
Edu	0.008(0.033)		
Work	0.685(0.156)***		
Income	0.001(0.004)		
Town	-0.043(0.164)		
Recre	-0.360(0.090)***		
fire_mn	-0.211(0.141)		
Cause	0.000(0.000)		
LogLikelihood	-4690.814		
N observations	397		
N choice sets	16		
R^2	-0.467		

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

***p<0.01 ** p<0.05 *p<0.10 SDPD: Std. Dev. of Parameter Distributions

Table 5. Choleski decomposition (lower triangle matrix) and correlation (upper off-diagonal) results

	CL_BB	CL_PB	CL_CG	DG_LINS	DG_IRRU	DG_IRRS	DE_MED	DE_HIGH	DE_VHIGH
CL_BB	0.74***	-0.25	-0.24	-0.54	-0.58	-0.58	-0.18	-0.70	-0.45
CL_PB	-0.25*	0.98***	0.50	0.54	-0.56	-0.24	-0.61	-0.28	-0.36
CL_CG	-0.19*	0.36***	0.67***	0.16	-0.09	0.43	0.25	0.03	-0.18
DG_LINS	-0.18***	-0.23***	0.13	0.07	0.87	0.75	0.79	0.77	0.56
DG_IRRU	-0.24**	-0.29**	0.05	0.01	0.15	0.74	0.67	0.79	0.56
DG_IRRS	-0.26**	-0.18**	0.25***	-0.16	0.07	0.11	0.66	0.69	0.49
DE_MED	-0.11	-0.42***	0.38***	-0.06	0.02	-0.22	0.08	0.41	0.22
DE_HIGH	-0.65***	-0.43***	0.08	0.10	0.09	0.27*	0.20	0.32**	0.87
DE_VHIGH	-0.49***	-0.53***	-0.08	0.04	-0.13	0.52***	0.25	0.48***	0.26

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

Table 6. RPL models with a mixture of normals with correlated parameters

Variables	Discrete Mixture Model (RPL with a mixture of normals) HIGH attribute			Discrete Mixture Model (RPL with a mixture of normals) VHIGH atribute		
	Coef.	**SDPD**	**Adj.**[a]	**Coef.**	**SDPD**	**Adj.**[a]
	Fire-related attributes					
CL_BB	0.325(0.057)***	-0.572(0.060)***	0.722	0.363(0.051)***	0.451(0.059)***	0.291
CL_CG	0.419(0.062)***	0.700(0.069)***	0.816	0.035(0.064)	-0.942(0.067)	-0.037
CL_PB	-0.347(0.056)***	-0.416(0.073)***	0.050	-0.470(0.062)***	-0.544(0.061)***	-0.542
DG_LINS	-0.072(0.045)	0.151(0.060)***	-0.110	-0.0468(0.047)	0.194(0.060)***	-0.135
DG_IRRU	0.097(0.043)***	-0.020(0.060)	0.059	0.0106(0.054)	0.305(0.069)***	-0.078
DG_IRRS	-0.063(0.060)	-0.528(0.062)***	-0.101	-0.0523(0.057)	0.536(0.075)***	-0.141
DE_MED	0.076 (0.042)	-0.012(0.069)	-0.488	-0.0304(0.050)	-0.266(0.064)***	0.106
DE_HIGH				0.565(0.042)***	0.0527(0.164)	0.701
DE_VHIGH	0.530(0.057)***	-0.797(0.059)***	-0.034			
DE_HIGH A	0.530(0.047)***	-0.198(0.069)***	-0.034			
DE_HIGH B	-4.50(0.684)***	4.23(0.865)***	-5.064			
DE_VHIGH A				0.420(0.060)***	0.176(0.109)	0.556
DE_VHIGH B				-1.09(0.213)***	-2.75(0.205)***	-0.954
Probability A	0.662(0.030)***			0.458(0.038)***		
Probability B	0.338(0.030)***			0.542(0.038)***		
ASC	-0.378(0.096)		fixed	-0.496(0.098)***	Fixed	
COST	-0.0265(0.001)		fixed	-0.0271(0.001)***	Fixed	
LogLikelihood	-5155.27			-5128.85		
N observations	397			397		
N choice sets	16			16		
R^2		0.412		0.415		

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

***p<0.01 ** p<0.05 *p<0.10 SDPD: Std. Dev. of Parameter Distributions

Table 7. LC model

Variables	LCM												
	Class 1 Typical			**Class 2 Yea-saying**			**Class 3 Burnt-worried**			**Class 4 Against**			**Class 1-4**
	Coef.	**SDPD**	**Adj.[a]**	**Coef.**	**SDPD**	**Adj.[a]**	**Coef.**	**SDPD**	**Adj.[a]**	**Coef.**	**SDPD**	**Adj.[a]**	**Common SDPD**
Fire-related attributes													
CL_BB	9.918***	21.466***	50.714	1.189***	-0.715***	3.62	0.954***	n.s.	3.128	-0.433	n.s.	-7.632	1.579***
CL_CG	13.214***	n.s.	54.010	0.846***	-0.748***	3.277	0.953***	n.s.	3.127	-1.162**	2.622***	-8.361	1.311***
CL_PB	17.663***	10.692***	58.459	0.396***	-0.263**	2.827	0.267	n.s.	2.441	-5.604	n.s.	-12.803	0.740***
DG_LINS	5.375***	11.641***	19.533	0.483***	-0.314***	1.92	0.091	-0.780*	1.942	-1.929***	1.754***	-8.046	0.572***
DG_IRRU	5.459***	11.685***	19.618	0.417***	-0.294***	1.854	0.781***	n.s.	2.632	-1.835***	1.724***	-7.952	0.403***
DG_IRRS	3.324***	5.214***	17.482	0.537***	-0.278***	1.974	0.979***	-0.418**	2.83	-2.353***	2.010***	-8.47	0.563***
DE_MED	19.727***	6.405***	75.273	1.125***	0.419***	6.091	2.770***	2.080***	12.422	-1.749***	1.761***	-6.514	0.633***
DE_HIGH	21.893***	11.779***	77.440	1.772***	1.276***	6.738	3.334***	2.479*	12.986	-1.343***	1.061**	-6.108	1.240***
DE_VHIGH	13.927***	20.354***	69.473	2.069***	1.604***	7.035	3.548***	2.298*	13.200	-1.673***	1.946***	-6.438	1.046***
ASC	1.4193***	fixed		-0.2641	fixed		-0.520	Fixed		-0.635	fixed		
COST	-0.9753***	fixed		-0.005***	fixed		-0.050*	Fixed		-0.025***	fixed		
Class membership variables													
Edu	-0.434**			0.172			0.280			-0.018			
Work	0.018			-0.487**			-0.384			0.853***			
Income	-0.009			0.004			-0.011			0.016***			
Town	-0.888***			0.121			0.158			0.606			
Recre	-0.673***			0.188			0.079			0.406			
fire_mn	0.584**			0.337			-0.126			-0.795**			
Cause	0.211			0.057			0.498			-0.766**			
R^2	0.942			0.302			0.548			0.592			0.678
Class Size (%)	33.44%			25.02%			23.87%			17.67%			100%
LogLikelihood	3760.881												
N observations	397												
N choice sets	16												

*** p<0.01 ** p<0.05 *p<0.10 SDPD: Std. Dev. of Parameter Distributions

Table 8. Marginal willingness to pay and confidence intervals for RPL, DM and LC models. The models with several classes shows a weighted average.

Variables	**RPL**		**Discrete Mixture model (RPL with a mixture of Normals)**		**Discrete Mixture model (RPL with a mixture of Normals)**		**LC Model (all classes)**
			HIGH attribute		**VERY HIGH attribute**		
	Mean	**95% CI**	**Mean**	**95% CI**	**Mean**	**95% CI**	**Mean**
Fire-related attributes							
CL_BB	-6.93	-25.87; 11.11	27.20	16.37; 38.00	10.91	1.08; 21.45	134.83
CL_CG	-7.11	-24.74; 10.12	30.52	19.87; 41.76	-1.12	-12.50;10.37	131.08
CL_PB	-44.87	-64.76; -26.68	1.17	-8.82; 12.29	-19.91	-31.67; -9.16	54.26
DG_LINS	-21.72	-37.38; -5.31	-3.91	-12.60; 4.46	-5.14	-14.45; 3.70	59.00
DG_IRRU	-20.16	-35.97; -4.49	2.45	-6.79; 10.81	-3.10	-12.27; 6.24	99.65
DG_IRRS	-17.00	-33.58; -0.24	-3.65	-14.36; 6.43	-3.10	-12.27; 6.24	106.23
DE_MED	-10.00	-27.51; 7.04	-18.24	-36.83; 1.37	3.54	-9.06; 15.19	688.41
DE_HIGH	6.47	-11.45; 23.90	-65.06	-100.43; -27.85	25.71	14.32; 37.33	724.39
DE_VHIGH	9.72	-9.78; 30.23	-1.07	-21.28; 19.73	-10.00	-28.47; 8.44	731.65

Table 9. Marginal willingness to pay and confidence intervals for LC model- class-by-class mWTP

Variables	Class 1- Typical		Class 2- Yeah saying		Class 3- Burnt – worried		Class 4- Against	
	Mean	**95% CI**	**Mean**	**95% CI**	**Mean**	**95% CI**	**Mean**	**95% CI**
Fire-related attributes								
CL_BB	53.79	36.45; 80.07	652.31	372.98; 1071.82	63.24	43.23; 84.75	-347.83	-694.20; -61.64
CL_CG	57.24	36.86; 86.72	652.93	385.71; 1102.53	63.00	41.99; 83.66	-376.14	-717.71: -85.33
CL_PB	61.89	40.57; 92.58	508. 62	287.94; 867.80	49.05	28.84; 68.56	-596.50	-1222.69; -47.49
DG_LINS	20.62	12.01; 32.32	403.06	193.85; 692.01	38.69	21.10; 57.87	-328.10	-469.29; -207.22
DG_IRRU	20.67	12.53; 32.09	587.76	311.51; 926.67	52.43	35.75; 69.92	-323.01	-470.26; -207.64
DG_IRRS	18.36	10.94; 28.32	589.67	348.35; 973.48	56.24	38.85; 74.93	-344.52	-503.82; -222.98
DE_MED	79.82	52.36; 118.48	2594.00	1747.17; 4095.35	250.03	213.97; 292.56	-265.91	-391.47; -156.97
DE_HIGH	81.93	54.91; 120.97	2712.80	1834.34; 4358.40	261.03	224.18; 307.26	-249.37	-383.81; -140.70
DE_VHIGH	73.56	48.92; 109.11	2757.37	1883.83; 4365.56	265.32	227.31; 309.60	-261.33	-404.97; -145.20

Figure 1. Example of a choice card

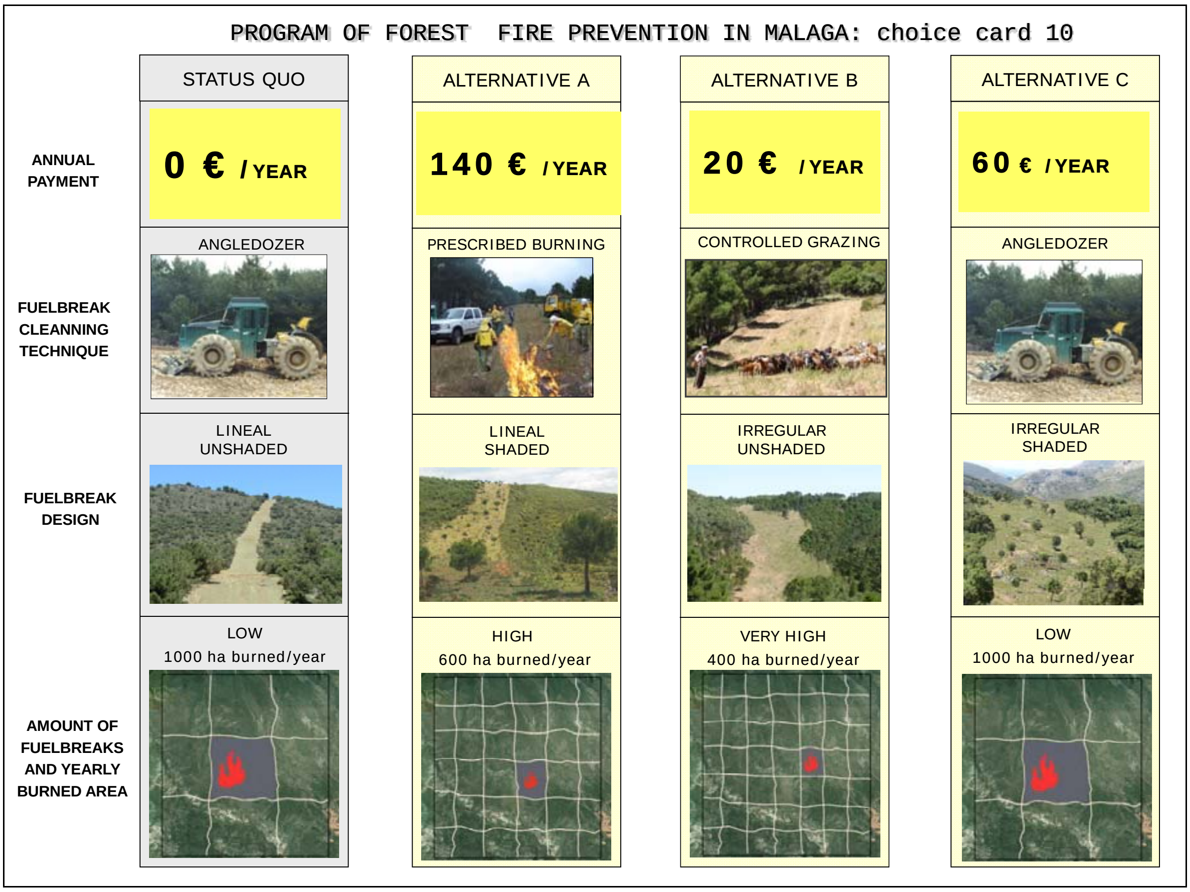


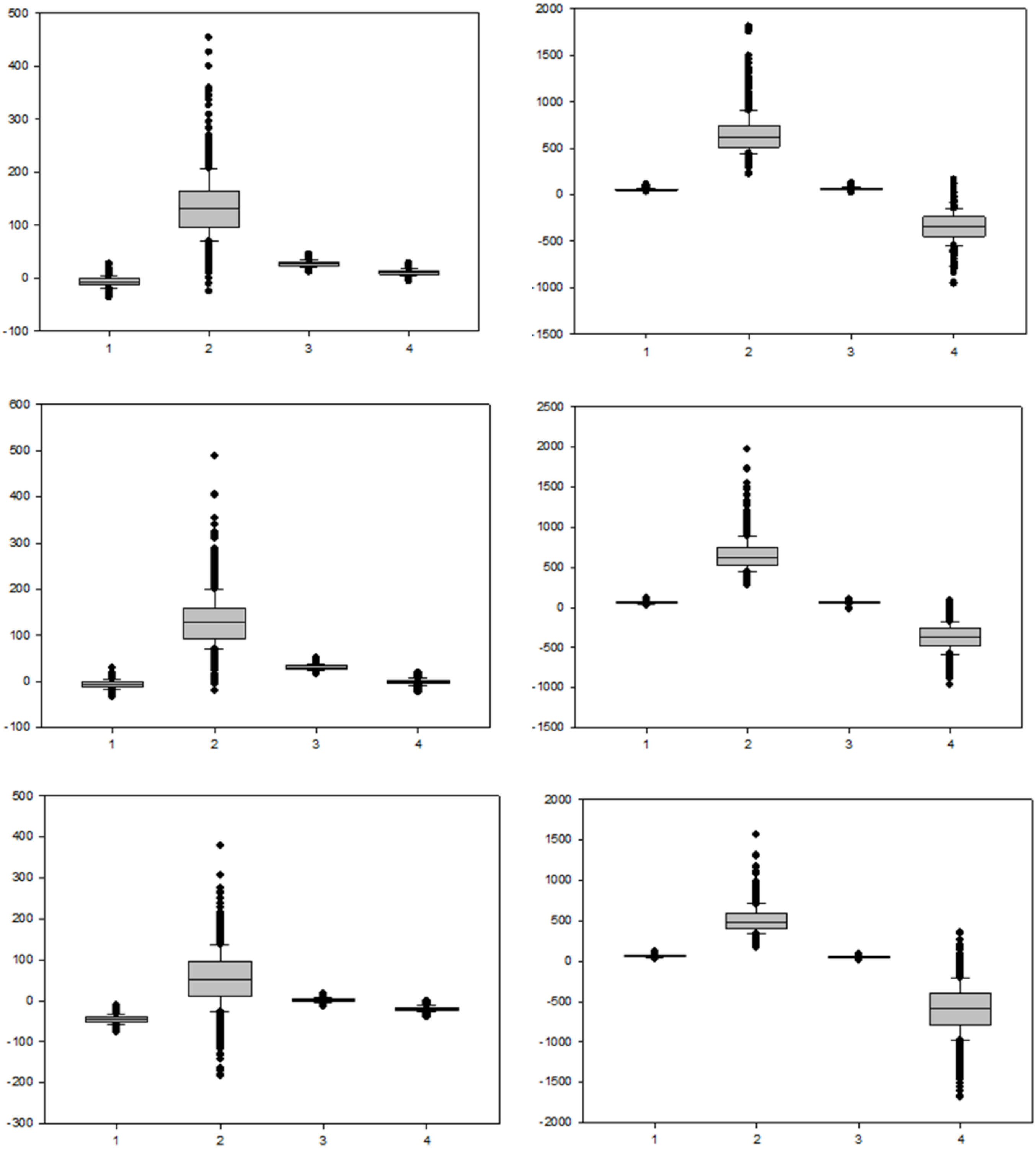
Figure 2. Dispersion of mWTP (in euros) for fuel break cleaning technique.

Attribute | **General results*** | **Class results****

CL_BB

CL_CG

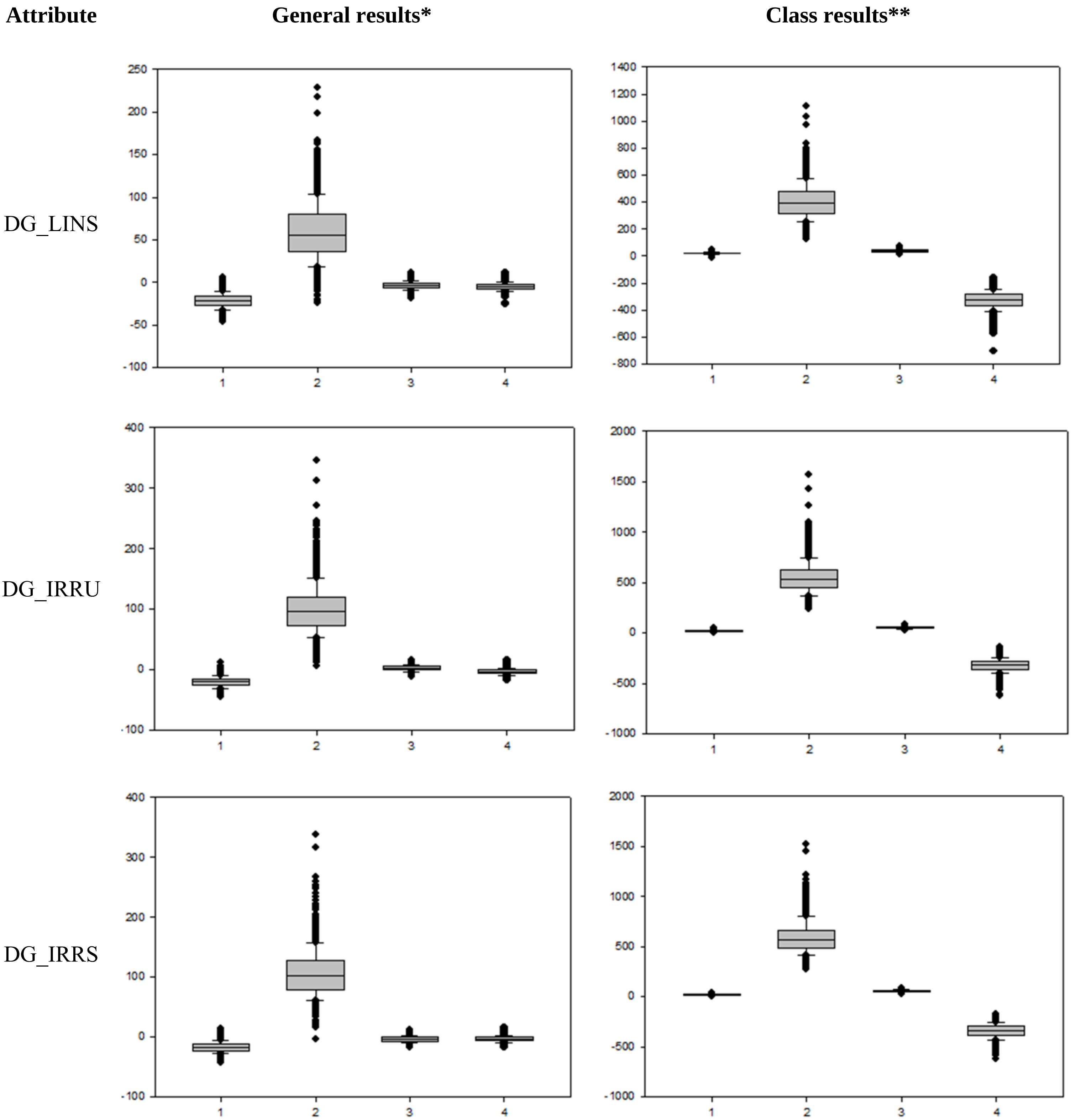
CL_PB



* Note: 1= RPL; 2= LCM (overall); 3= Mixture model for HIGH attribute; 4= Mixture model for VHIGH attribute

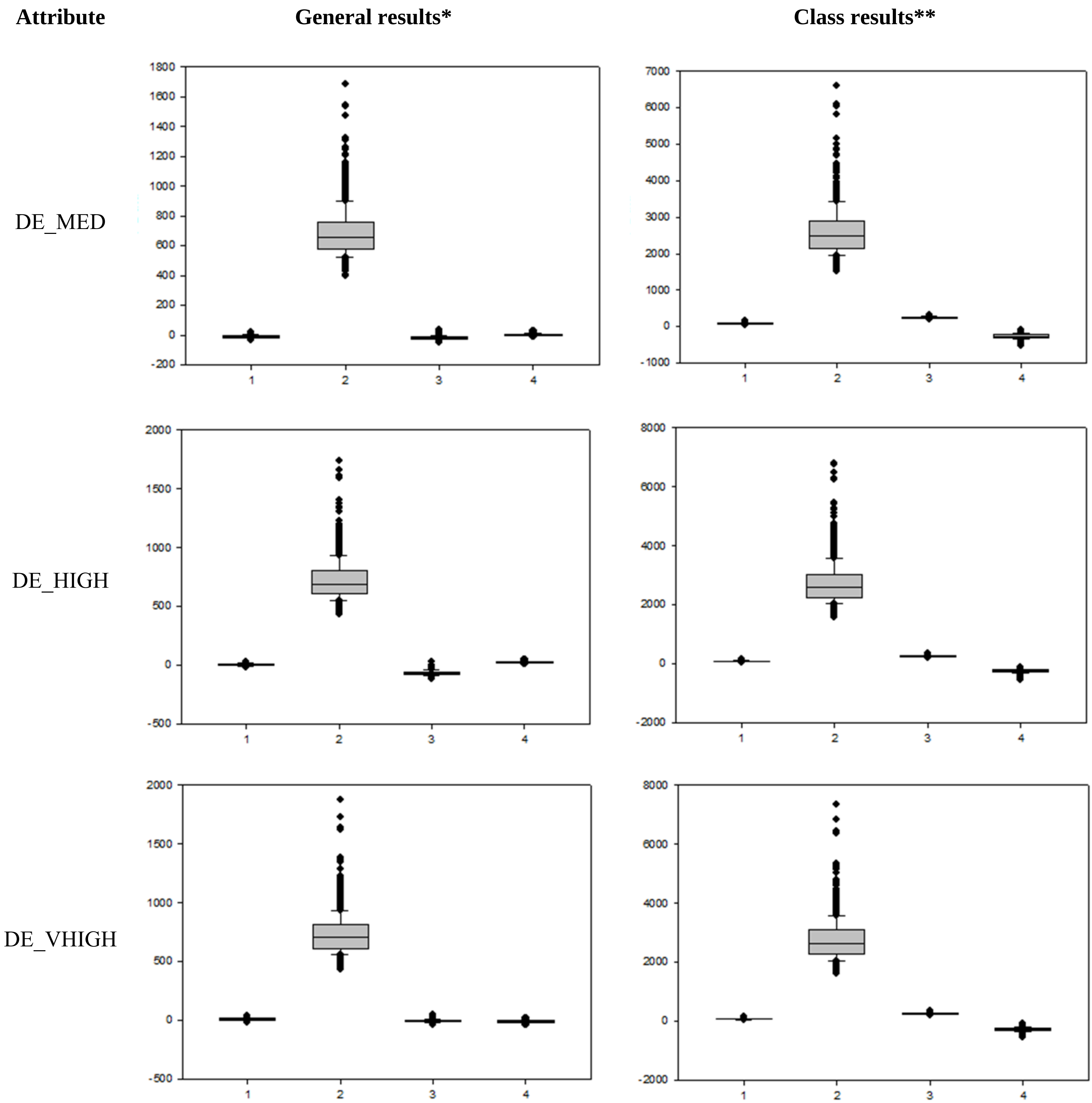
** Note: 1= Typical; 2= Yea-saying; 3= Burnt-worried; 4= Against

Figure 3. Dispersion of mWTP (in euros) for fuel break cleaning design



* Note: 1= RPL; 2= LCM (overall); 3= Mixture model for DE_HIGH attribute level; 4= Mixture model for DE_VHIGH attribute level
** Note: 1= Typical; 2= Yea-saying; 3= Burnt-worried; 4= Against

Figure 4. Dispersion of mWTP (in euros) for fuel break for density of fuel breaks



* Note: 1= RPL; 2= LCM (overall); 3= Mixture model for DE_HIGH attribute level; 4= Mixture model for DE_VHIGH attribute level
** Note: 1= Typical; 2= Yea-saying; 3= Burnt-worried; 4= Against