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4

5 UNDERSTANDING THE HETEROGENEITY OF SOCIAL PREFERENCES FOR FIRE
6 PREVENTION MANAGEMENT

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23

24 **Abstract**

25 The forest area burnt annually in the European Mediterranean region has more than doubled
26 since the 1970s. In these forests, the main preventive action consists of forest
27 compartmentalization by fuel break networks, which entail high costs and sometimes
28 significant negative impacts. While many studies look at public preferences for fire
29 suppression, this study analyses the heterogeneity of social preferences for fire prevention.

30 The visual characteristics of fire prevention structures are very familiar to respondents, but
31 their management is unfamiliar, which raises specific attention in terms of analysing
32 preference heterogeneity. A random parameter logit model revealed large heterogeneity and
33 preference for traditional heavy machinery, maintaining linear unshaded fuel breaks at a high
34 density. A latent class model showed that this may be reflected by a third of the population
35 preferring lighter machinery and shaded irregular fuel breaks; a quarter of the population not

36 treating the budget constraint as limiting, another quarter only being worried about the area
37 burnt and the remaining group being against everything. Finally, a discrete mixture model
38 revealed extreme preference patterns for the density of fuel breaks. These results are
39 important for designing fire prevention policies that are efficient and acceptable by the
40 population.

41

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

44 **UNDERSTANDING THE HETEROGENEITY OF SOCIAL PREFERENCES FOR**
45 **FIRE PREVENTION MANAGEMENT**

46

47 **1. Introduction**

48 The ecosystem services provided by Mediterranean forests – such as protection against
49 erosion or biodiversity conservation - are increasingly recognized (FAO, 2013). However,
50 these services are under risk of degradation, with forest fires as the most important threat to
51 Mediterranean forest ecosystems today (Ministry of Environment, 1998; Valbuena-Carabaña
52 et al., 2010). Every year forest fires in the European Mediterranean region attract media
53 attention and debate about forest management so as to minimize the environmental and social
54 damages, in particular when villages and infrastructure are affected. The annual burnt area in
55 the European Mediterranean region has more than doubled since the 1970s (Xanthopoulos et
56 al., 2006). Farmland abandonment is regarded as one of the main drivers of this situation
57 (Duguy et al., 2007; Loepfe et al., 2010; Pausas, 2004; Pausas et al., 2008; Vélez Muñoz,
58 2004) as the traditional rural mosaic that creates sufficient fuel fragmentation is becoming
59 scarce. The build-up of large and continuous fuel beds facilitates fire spread (Loepfe et al.,
60 2010; Pausas, 2004), and forest fires are expected to be aggravated by climate change and
61 resultant longer dry summer periods (Mouillot et al. 2002, Morriondo et al. 2006, Pausas,
62 2004). The losses due to forest fires are not only related to ecosystems, but also to human
63 lives and infrastructure, with a wide array of interrupted or diminished ecosystem services
64 flowing to society (Barrio et al., 2007).

65

66 In the Mediterranean region, wildfire spread is mainly reduced through the forest
67 compartmentalization by fuel break networks. These structures traditionally are linear strips
68 where the trees are disposed of and the vegetation is removed down to the mineral soil with

69 mechanical tools. The costs of creating and maintaining such networks are high and the
70 negative impacts (landscape impact and soil erosion) can be locally significant. Therefore,
71 some public agencies are testing new designs for these structures as well as alternative
72 maintenance tools to lower both the negative impacts and the costs. Fire prevention plans are
73 developed by public agencies and are mainly based on technical and budget criteria (De
74 Castro et al., 2007). This may be the best strategy in so far that the differences in
75 management are small, technical and not visible to the general public. However, fire
76 prevention has large impacts on the visual perception of the landscape, and forest fires as an
77 environmental problem attract much attention from the population (IESA/CSIC, 2007).
78 Therefore, from a welfare economic point of view, public preferences for fire prevention
79 should be taken into account when designing fire prevention strategies.

80

81 The influence of fire on the social value of forests was initially addressed in Vaux et al.
82 (1984), where changes in recreational values were studied. Hesseln et al. (2004) and Starbuck
83 et al. (2006) also pursued this research avenue. Somewhat related, other valuation studies
84 focused on the estimation of citizens' WTP for protecting certain areas or reducing wildfire
85 risk in the landscape as a whole (Loomis and González-Cabán, 1994; Loomis and González-
86 Cabán, 1998; Riera and Mogas, 2004; Winter and Fried, 2001). In recent years, the focus has
87 broadened to explore citizens' preferences for different strategies aimed at diminishing
88 wildfire risk, such as mechanical fuel reduction, prescribed burning or biomass for energy
89 (González-Cabán et al., 2007; González-Cabán et al., 2004; Kaval et al., 2007; Loomis and
90 González-Cabán, 2008; Loomis et al., 2004; Loomis et al., 2005; Loomis et al., 2009; Soliño,
91 2010; Soliño et al. 2010 and 2012; Walker et al., 2007). Holmes et al. (2012) explore risk
92 perception and assess the trade-offs between wildfire risk and damage in public fire
93 prevention systems. Calkin et al. (2012) investigate the trade-offs fire managers are willing to

94 make under competing strategic suppression objectives. The fire issue can also be explored in
95 a broader context, assessing the trade-offs between fire prevention and many ecosystem
96 services at the same time (Mavsar et al., 2013) as well as between fire and different climate-
97 sensitive attributes (Riera et al., 2007).

98

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

110

111 Two complementary approaches may be distinguished to tackle the issue of preference
112 heterogeneity. The first consists in assessing the observable component of heterogeneity by
113 incorporating explanatory variables in the choice models (Choi and Fielding, 2013).
114 Interactions of specific socioeconomic covariates with either site attributes or alternative-
115 specific constants allow the capture of the observable component of heterogeneity (Choi and
116 Fielding, 2013; Hynes et al., 2008). Socio-demographic characteristics are useful for
117 interpretation (Hess et al., 2005), although assumptions are indeed required in the selection of
118 the variables employed for these interaction terms; the variables must be relevant to the

119 choice context being examined and they must have acceptable explanatory power (Boxall and
120 Adamowicz, 2002). Attitudinal characteristics are increasingly being used as criteria for
121 population segmentation or as explanatory variables for econometric models (Choi and
122 Fielding, 2013; Lundhede et al., 2014). Fire related valuation studies typically include
123 socioeconomic covariates such as income, education or age (Loomis et al., 2009; Mavsar et
124 al., 2013), but also attitudinal questions to gain insight on respondents' preferences. Fire
125 related questions such as perceived fire danger, perceived fire frequency by the respondents
126 (Kaval et al 2007), witnessing fires or experiencing the negative consequences of forest fires
127 have proved to be significant in determining WTP for fire prevention or biomass reduction
128 activities (Loomis, 2008; Walker et al., 2007).

129

130 A complementary approach to the previous consists in assessing the unobserved
131 heterogeneity of preferences through the systematic component of utility. Random parameter
132 logit models (RPL), latent class models (LC) and discrete mixture models (DM) are three
133 ways of doing so (Birol et al., 2006; Campbell et al., 2014; Doherty et al., 2013; Morey et al.,
134 2006; Provencher and Bishop, 2004; Train, 2009) and are applied in the current study. These
135 modelling approaches may provide complementary views to understand the unobserved
136 heterogeneity at different levels: average population, population classes and management
137 attributes. This is of particular importance for fire prevention due to the characteristics
138 hereof: both the measures and consequences are very concrete but while the consequences are
139 very familiar to respondents, yet the measures are often not very familiar even if they have a
140 high impact on the landscape, and consequently on people.

141

142

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

150

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

160

161 **2. Forest fires and fire prevention in the Mediterranean region**

162

163 Paleocological studies suggest that fires are natural in the Mediterranean region (Pausas et
164 al., 2008). Nevertheless, the increase in the number of fires and burnt area during the 20th
165 century sometimes surpasses the capacity of these ecosystems to recover after the fire (Pausas
166 et al., 2008). The social demand for environmental protection together with the consideration
167 of forest ecosystems as a public good impelled the launching of permanent protection

168 programmes against forest fires (Vélez Muñoz, 2004). The efforts evolved towards a policy
169 centred in emergency suppression measures, based on very sophisticated equipment with high
170 costs. As a result, fire suppression capacity in southern European countries has been
171 improved since the 1990s, allowing for a reduction in the burnt area in relatively easy fire
172 seasons. However, fire suppression policies have shown their limited ability to remove the
173 risk of major disasters when not coupled with appropriate fuel management strategies
174 (Xanthopoulos, Caballero et al. 2006; Rigolot, Fernandes et al. 2009). The excessive focus on
175 fire suppression instead of fire prevention resulted in reduced availability of financial
176 resources for long term preventive actions (Montiel and San Miguel, 2009), which are less
177 spectacular and need continuous maintenance over time. It is expected that this trend will
178 slowly change in light of the widely recognized role that prevention plays in fire protection
179 (Tàbara et al. 2003), being maybe the most effective approach to face wildfires (FAO, 2013).
180 Not only the researchers or land managers, but also the society, are progressively demanding
181 a shift towards fire prevention management (Moyano et al., 2006).

182
183 Fire prevention is a group of activities aimed at reducing or avoiding the probability that a
184 fire starts and also at limiting its effects if it takes place (Vélez Muñoz, 2000). Fire prevention
185 entails two complementary approaches: social and physical. The social dimension aims at
186 diminishing the causes of anthropogenic fires (Martínez et al., 2009), while the physical fire
187 prevention deals with the biomass for the purpose of modifying potential fire behaviour
188 (Husari et al., 2006) by decreasing fire intensity (Martinson and Omi, 2003), wildfire
189 severity, rate of spread and, therefore, the likelihood of extreme fire behaviour (Husari et al.,
190 2006; Piñol et al., 2007; Reiner et al., 2009; Schmidt et al., 2008). It is the latter that is in
191 focus in the present paper.

192

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

199

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

209

210 **3. Material and Methods**

211

212 **3.1 Survey design, case study description and data collection**

213 Citizens' preferences for environmental and natural resource management have traditionally
214 been studied by natural resource economists for several purposes (e.g. cost-benefit analysis,
215 decision-making, welfare assessment, etc). Several choice modelling techniques (ranking,
216 rating and discrete choice) have been developed to do this. In this study, data obtained from a
217 ranking experiment to explore social preferences for three main fire-related attributes in fuel

218 break management (Varela et al., 2014) was used as a discrete choice experiment using only
219 the best rank as suggested by Caparrós et al. (2008).

220

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

234

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

242

243 The choice sets utilized in our study were prepared following an optimal in difference design
244 as proposed by Street et al. (2005) and Street and Burgess (2007). The design consisted of
245 sixteen choice sets and each respondent was asked to evaluate all sixteen. Evaluating the d-
246 error ex-ante for a multinomial main effect model gave a d-error of 0,008894. Choice cards
247 showed an identical status quo option which corresponds to the current most widespread
248 management in Málaga, (the province of Andalucía, Southern Spain) where the survey was
249 conducted plus three alternative management programs. An example of the choice cards is
250 shown in Figure 1¹.

251

252 [Table 1 around here]

253 [Figure 1 around here]

254

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

263

264 [Table 2 around here]

265 Málaga is a coastal province of Andalucía with more than 77% of its area having
266 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.

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

271

272 **3.2 Econometric models**

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

281

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

288

289 The continuous representation of preference in the random parameter logit (RPL) model
290 introduces taste variation by assuming that each member in the sample has a different set of
291 utility parameters. The RPL model controls for heterogeneity, assuming that each individual

292 in the sample has a different set of utility parameters and, therefore, assessing the
293 distributional impacts across individuals. Furthermore, RPL specifications can allow for
294 correlations across random parameters when the likelihood of correlation in preferences for
295 the different attributes may be significant (see e.g. Campbell et al., 2014; Hanley et al., 2010;
296 Hynes et al., 2008). RPL models fit best when individuals' preferences distribute
297 continuously and can be described by continuous distribution functions like the normal
298 distribution.

299

300 In contrast, latent class (LC) models offer an alternative perspective to the RPL, replacing the
301 continuous distribution with a discrete distribution (Green and Hensher, 2010). This approach
302 is suitable when preference variation can be explained in the form of clusters, i.e. taste
303 intensities take place over a finite number of classes of individuals rather than over
304 continuous value distributions. LC models impose more structure on the choice model but in
305 return allow for descriptions of segment heterogeneity in the data. Latent class approaches
306 make use of two sub-models, one for class allocation, and one for within class choice (Hess
307 2007). The former models the probability of an individual being assigned to a specific class
308 as a function of attributes of the respondent and possibly of the alternatives in the choice set.
309 The within class model is then used to compute the class-specific choice probabilities for the
310 different alternatives, conditional on the tastes within that class (Hess 2007). LC models
311 presented an initial caveat due to the underlying assumption of within group homogeneity.
312 Undoubtedly, it is improbable to expect that all individuals with identical socioeconomic
313 characteristics will have the same preferences (Bujosa et al. 2010). Therefore, a natural
314 extension of the fixed parameter latent class model is a random parameter class model which
315 allows for another layer of preference heterogeneity within a class (Greene and Hensher
316 2010). The LC model in this study simultaneously classifies respondents in a number of

317 classes depending on a number of covariates and estimates utility parameters based on
318 random parameter model procedure, allowing for a common random effect for all the classes
319 and a specific random component for each class (Justes et al., 2014; Soliño and Farizo, 2014).

320

321 Several authors have compared the performance of RPL and LC approaches to choice data to
322 determine which one fits the data better and to examine differences in welfare estimates
323 (Birol et al., 2006; Boeri et al., 2011; Boxall and Adamowicz, 2002; Broch and Vedel, 2012;
324 Bujosa et al., 2010; Colombo et al., 2011; Greene and Hensher, 2003; Holmes et al., 2012;
325 Hynes et al., 2008; Kosenius, 2010; Provencher and Bishop, 2004; Shen, 2009). The
326 empirical results show there is no clear pattern indicating which approach is superior and the
327 issue of which model provides the best description of the data is likely to be data dependent
328 (Boeri et al., 2011). Bujosa et al. (2010), Hensher and Greene (2010) and Yoo and Ready
329 (2014) favour the use of latent class random parameter models, since they found that this
330 model delivered the best overall fit.

331

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

342

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

351

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

365

366 **4. Results**

367

368 **4.1 Perceptions on forest fires: importance and causality**

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

388

389 **4.2 RPL, LC and DM results**

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

393

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

401

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

407

408 As the fire-related attributes in the model have been effects-coded, it is also worth noting that
409 for each attribute the magnitude of the omitted base case level coefficient is assumed to be
410 equal to the negative sum of the utility weights for the other estimated categories (Louviere et
411 al., 2000; Lusk et al., 2003). Following Dominguez-Torreiro and Soliño (2011), an additional
412 column representing the adjusted marginal utility gains from the base level situation for each
413 of the levels of the effects-coded fire-related attributes has been included in tables 4,6 and 7
414 to make clearer the interpretation of the results.

415

416 **4.2.1 RPL results**

417 Table 4 shows the results of the first model estimated, an RPL model with panel structure,
418 500 Halton draws and allowing for correlation among the random parameters. All the
419 management attributes were modelled as random parameters according to a normal
420 distribution. Cost attribute and the ASC remained constant. The model was estimated with
421 NLOGIT 4.0 software (Greene, 2007). Observing the values for the adjusted coefficients, the
422 three cleaning tools (CL_BB, CL_CG, CL_PB) are significant, retrieving similar and
423 negative values for light machinery (CL_BB) and controlled grazing (CL_CG), while
424 prescribed burning (CL_PB) holds the most negative value among the three cleaning tools.
425 Moving to the design-related attribute levels (DG_LINS; DG_IRRU, DG_IRS), only the
426 linear shaded designs (DG_LINS) retrieve significant and negative values, indicating a
427 preference for the traditional linear unshaded designs (DG_LINU). The remaining design
428 fire-related attribute levels are non-significant, suggesting that the design of preventive
429 structures plays a minor role in shaping social preferences. When it comes to the density of
430 fuel breaks (DE_MED; DE_HIGH; DE_VHIGH) (that is coupled with a decrease in the burnt
431 area), medium (DE_MED) and very high density levels (DE_VHIGH) retrieve significant
432 values, negative and positive, respectively, while the high density level (DE_HIGH) remains
433 non-significant.

434

435 The cost attribute shows a negative value as expected, while the negative value of the ASC
436 indicates that *ceteris paribus* respondents experience a disutility from the SQ situation and
437 would be willing to move to any of the proposed alternatives. Despite extensive testing of
438 interactions between random parameters and the covariates we hypothesized could contribute
439 to explain systematic taste variation, no significant outcome was provided. When new policy

440 designs are investigated it is of interest to know which respondent characteristics increase the
441 probability of agreeing with the “policy-on” options and which with the probability of the
442 “policy-off” option (Colombo et al., 2009). The interaction of some of these covariates (Table
443 2) with the ASC retrieved significant results that contribute to explain respondents’
444 willingness to move from the SQ situation to alternative scenarios.

445

446 [Table 4 around here]

447

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

452

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

462

463 [Table 5 around here]

464

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

474

475 **4.2.2 Discrete mixture results**

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

480

481 Those models were estimated using Biogeme software (Bierlaire, 2003). Observing the
482 adjusted coefficients, DE_HIGH retrieves significant and negative values for its two
483 distributions, with 34% of the sample showing very negative mean values for the parameter,
484 indicating that an important disutility is experienced for the DE_HIGH parameter, even if it is
485 a small share of the population that experiences it. DE_VHIGH attribute levels show both
486 positive and negative mean values, with 54% of the respondents attached to the latter. We
487 note that the negative values are numerically much higher than the positive ones for the
488 DE_VHIGH parameter. These models detected that some people hold very negative
489 preferences for increases in the density of fuel breaks. Preferences of risk avoiders could be

490 ascribed to the positive mean distributions while landscape-aware profiles would be allocated
491 into the negative mean distributions of the parameters. Finally, allowing for mixed
492 distributions for the density levels also had an impact on the estimates of other coefficients,
493 especially for light machinery (CL_BB), which shows results more according to our
494 expectations resulting from the focus group sessions. This may be caused by the RPL model
495 allowing for correlated parameters, and if the parameters for fuel break density do not capture
496 the heterogeneity of the population they will carry over to the other variables too.

497

498 [Table 6 around here]

499

500 **4.2.3 LC results**

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

514 [Table 7 around here]

515

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

520

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

534

535 Class 2 shows similarities with Class 1 in terms of the relative importance of the taste
536 parameters within the class: density fire-related attributes show the highest values, followed
537 by cleaning techniques. The distinctive feature of this group is their relatively low
538 sensitiveness to the cost attribute. This leads us to conclude that respondents in this class did
539 not consider their budget restrictions and accordingly we named it the *yea-saying* class. Yea-

540 saying behaviour was also found by Holmes et al. (2012) among respondents evaluating
541 wildfire protection programmes. In their case, responses from individuals less likely to have
542 personal experience of the effects of wildfire reflected a way of simplifying decisions,
543 ignoring some fire-related attributes (cost among them) while expressing support for wildfire
544 protection programs. We hypothesized that topics such as forest fires that have a high social
545 relevance, are more prone to subordinate economic preferences in favour of expressive
546 motivations. Unemployed respondents in the sample are less likely to belong to this class,
547 probably because their budget constraints are less likely to lead them to yea-saying
548 behaviour.

549

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

556

557 Finally, Class 4 is the most dissimilar when compared with the other three classes, showing
558 negative values for all the levels of the fire-related attributes, being tagged as the *against*
559 class. The respondents experience a significant disutility when moving from the SQ scenario.
560 Because protest responses were previously removed, we hypothesize that disutility has a
561 different origin. Respondents in this class neither refused to participate in the hypothetical
562 market nor showed distrust in the administration (as most of the protesters did). The work
563 variable plays the biggest role in determining class membership, with unemployed people
564 having a higher probability of belonging to this class. On the contrary, people considering

565 forest fires as a very relevant environmental problem, and also those considering arson and
566 land use change as the main drivers of forest fires, are less likely to be allocated to this group.

567

568 **4.2.4 Marginal WTP results**

569 Individuals' coefficients for the fire related attributes are converted into marginal willingness
570 to pay (mWTP) following the Lusk et al. (2003) formula for effect-coded attributes and
571 applying the Krinsky and Robb (1986) procedure with 1,000 replications for the mean and
572 95% confidence intervals. The estimates for the RPL, DM models and LC models are
573 reported in Tables 8 and 9 and in Figures 2-5²:. The mean negative values in RPL are
574 disentangled in LC estimates, where the *against* class shows distinctively negative values
575 while the *yea-saying* class expresses rather high WTP values when compared with the other
576 classes. We notice that this leads to a higher overall WTP in the LC model than for the RPL
577 model for all the estimates. However, the LC model allows to identify the source of these
578 high WTP estimates in the yea-saying class. The DM models shed light on the preferences for
579 the density attribute levels showing that negative mean WTP estimates are obtained for the
580 high densities. This is more in line with what was observed in the focus groups in relation to
581 the role of the design attributes.

582 [Insert Figures 2-4 around here]

583

584 **5. Concluding discussion**

585 Forest fire is a large problem in the Mediterranean area and receives a lot of media attention.
586 This causes people to have strong feelings on the issue, yet often on an uninformed basis.
587 Consequently, resource use on fire prevention and suppression is affected by not only
588 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).

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

600

601 **5.1 Preferences for fire prevention and management implications**

602 Overall we find that that people are not indifferent as to how fire prevention is carried out. On
603 average we observe a negative marginal WTP for prescribed burning instead of the classic
604 scarification with angledozer and also that linear unshaded fuel break designs are preferred
605 over shaded and irregular designs. Policy makers are reluctant to apply prescribed burning
606 due to expected rejection by the population (Xanthopoulos et al. 2006) as also our RPL model
607 shows. However, the LC model shows that rejection is not general, with more than half of the
608 population in favour of the use of this management tool. Similarly, this model shows that
609 softer fuel break cleaning techniques like backpack brush-cutters and controlled grazing are
610 also preferred over the classic techniques by most of the population. This supports the
611 ongoing initiatives employing controlled grazing as a complementary tool for fuel
612 management (Ruiz-Mirazo et al., 2011). This share of the population that seem to be these
613 opposed to changes in the current management of prevention structures, we identify them as

614 more likely being unemployed, not recreating in nature much, and less likely seeing forest
615 fires as the main environmental problem or caused by the main reasons argued in the media.
616 On this basis it is difficult to affirm that it is a specific group of people who can be targeted in
617 policy making. Rather it calls for further analyses of what causes the opposition of prescribed
618 burning.

619

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

626

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

634

635 Finally, some uncertainties still remain about how to relate those findings to the articulation
636 of fire prevention policies and communication strategies. Advocating for changes in fire
637 prevention needs committed politicians able to set up long-term plans to reduce biomass
638 content at a landscape level and increased work on the human causes of forest fires. Change

639 in the traditional fire prevention structures is one of the measures within a broader view of
640 fire prevention measures. Therefore future research direction should aim to explore to what
641 extent citizens will support these changes.

642

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

650

651 **5.2 Comparison of heterogeneity models**

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

657

658 The important contribution of the LC model compared to the RPL approach is to better
659 capture the variation in preferences for specific segments of the population. This
660 segmentation let us characterize two extreme classes among the respondents whose
661 preferences have important implications in the mean welfare estimates, i.e. the *yea-saying*
662 class and the *against* class, that otherwise are not captured in the RPL model. This is
663 important as we would rather not to kick respondents out of the sample; but instead identify

664 the implication of the potential bias they may give (the yea-saying group). In the LC model
665 used here we estimated a standard deviation for each attribute within each class, that
666 resembles advanced RPL distributions although allowing for more flexibility than in the
667 typical LC models (e.g. Jacobsen et al., 2012). Furthermore, we included a common standard
668 deviation for all attributes across all classes. This is done to make classes more meaningful
669 with respect to the effect of attributes (Farizo et al., 2014; Vermont and Magidson, 2005)

670

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

678

679 Overall, the LC model might better capture our intuition about some of the respondents based
680 on our observations in the focus groups (i.e. burnt-worried class) and on evidences from the
681 literature (i.e. yea saying class as in Homes et al.,2012). Although it is not possible to choose
682 between the different models based on goodness of fit, as each of them provides with
683 different pictures of preferences and WTP (Yoo and Ready, 2014), our results are in line with
684 previous work favouring the latent class models (Bujosa et al.,2010; Hensher and Greene,
685 2010; Yoo and Ready,2014). This is likely a result of the valued good being rather unfamiliar
686 in implementation yet familiar in consequences. Still we would like to emphasize the role of
687 the other models to better capture different components of the heterogeneity. In the current
688 study we can see that the RPL model is good at unveiling the share of the population not

689 willing to move from the SQ scenario, which overall has a higher influence in the mean WTP
690 estimates than other segments of the population. Finally, DM models show reflect the impact
691 of considering extreme preference patterns for the density attribute, by retrieving mean
692 weighted WTP values for the attribute that reflect the very negative preferences held by a
693 share of the population.

694

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705

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970 **Tables and figures for “Understanding the heterogeneity of social preferences for fire**
 971 **prevention management”**

- 972
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988 **Table 1. Fire-related attributes and levels**
 989

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

990 *Status quo level.

991

992 **Table 2. Socioeconomics of the surveyed respondents**

Variable	Sample	Málaga population	Significance one- sample χ^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	

993

994

995

996 **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 1 st or 2 nd 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)

997

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

1002

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

	CL_BB	CL_PB	CL_CG	DG_LIN S	DG_IRR U	DG_IRR S	DE_ME D	DE_HIG H	DE_VHI GH
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

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1004

1005 **Table 6. RPL models with a mixture of normals with correlated parameters**

Variables	Discrete Mixture Model (RPL with a mixture of normals)			Discrete Mixture Model (RPL with a mixture of normals)		
	HIGH attribute			VHIGH attribute		
	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		

1006 ^a Adjusted marginal utility gains from the base level situation for the effects-coded attributes

1007 ***p<0.01 ** p<0.05 *p<0.10

SDPD: Std. Dev. of Parameter Distributions

1008

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













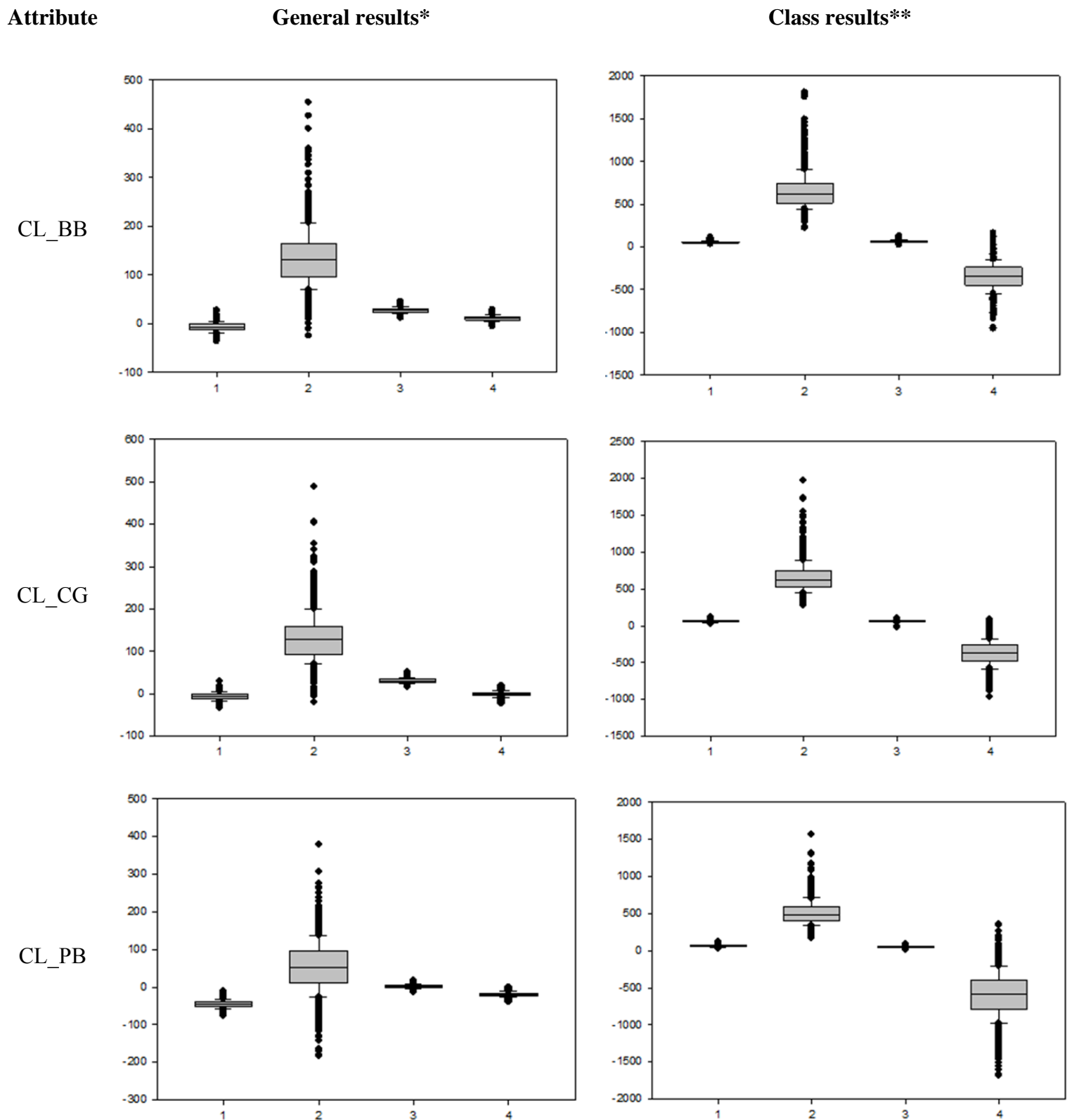
PROGRAM OF FOREST FIRE PREVENTION IN MALAGA: choice card 10				
	STATUS QUO	ALTERNATIVE A	ALTERNATIVE B	ALTERNATIVE C
ANNUAL PAYMENT	0 € /YEAR	140 € /YEAR	20 € /YEAR	60 € /YEAR
FUELBREAK CLEANING TECHNIQUE	ANGLEDOZER 	PRESCRIBED BURNING 	CONTROLLED GRAZING 	ANGLEDOZER 
FUELBREAK DESIGN	LINEAL UNSHADED 	LINEAL SHADED 	IRREGULAR UNSHADED 	IRREGULAR SHADED 
AMOUNT OF FUELBREAKS AND YEARLY BURNED AREA	LOW 1000 ha burned/year 	HIGH 600 ha burned/year 	VERY HIGH 400 ha burned/year 	LOW 1000 ha burned/year 

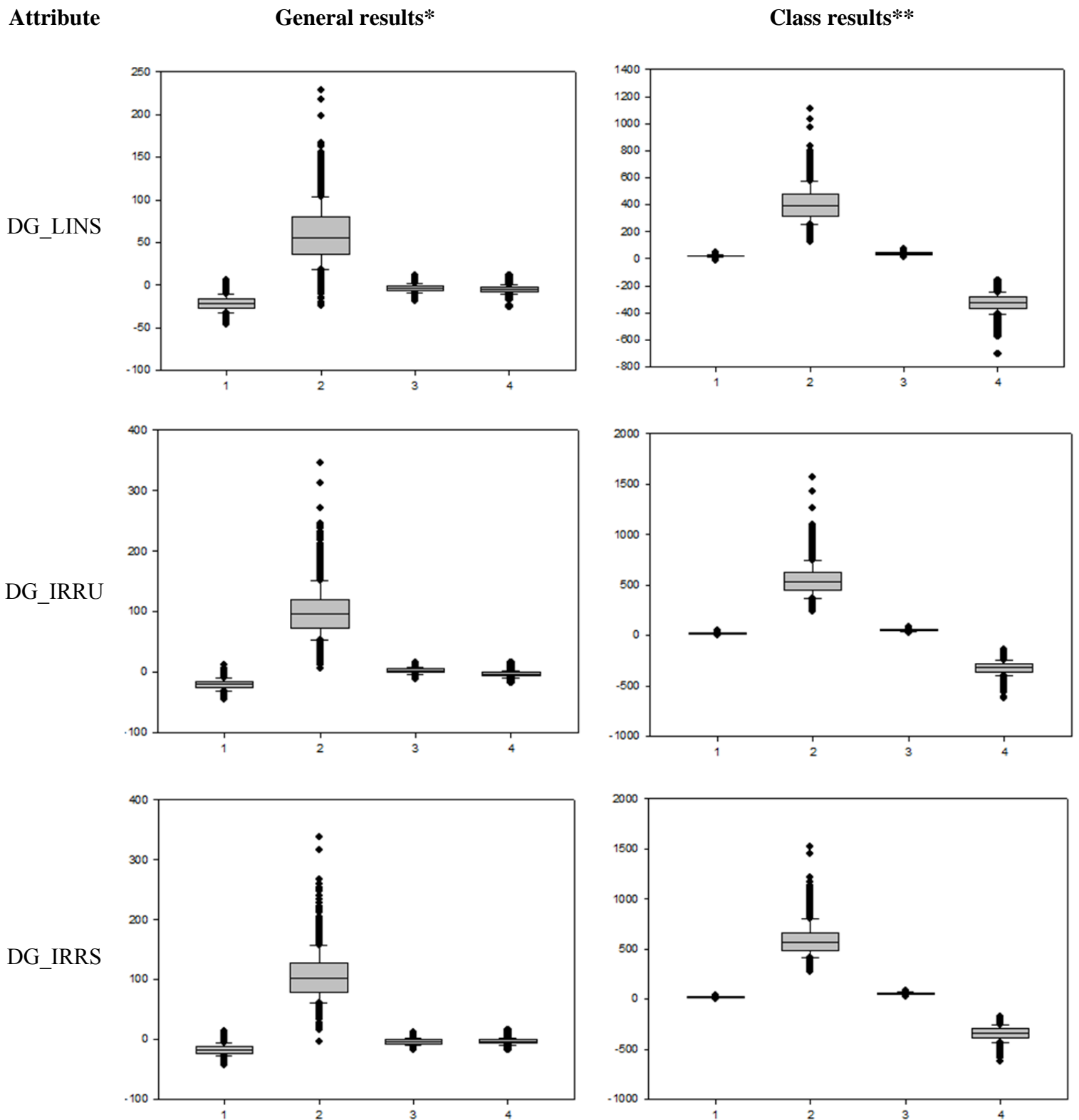
Figure 2. Dispersion of mWTP (in euros) for fuel break cleaning technique.



* 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

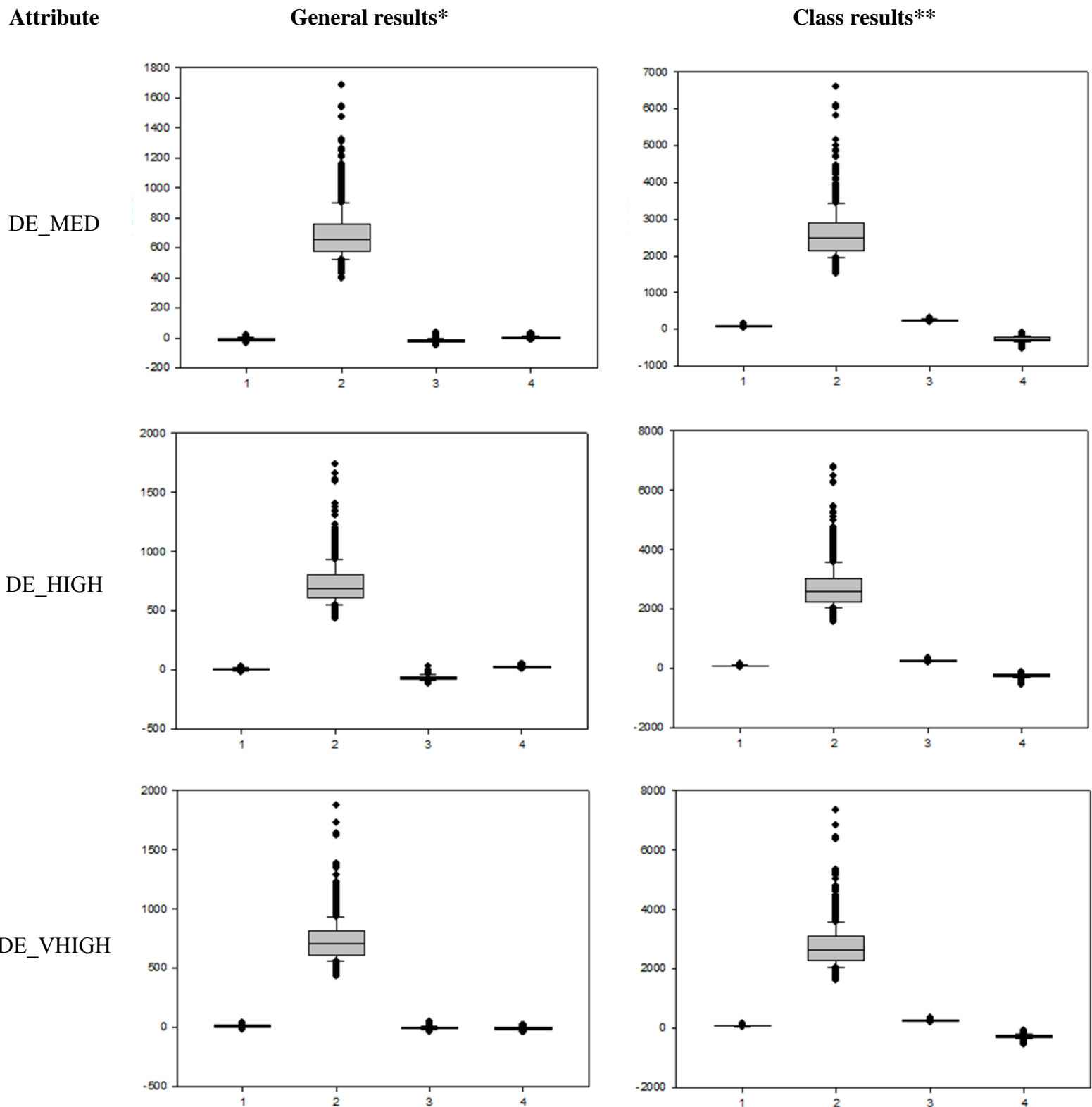
Figure 3. Dispersion of mWTP (in euros) for fuel break cleaning design



* 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