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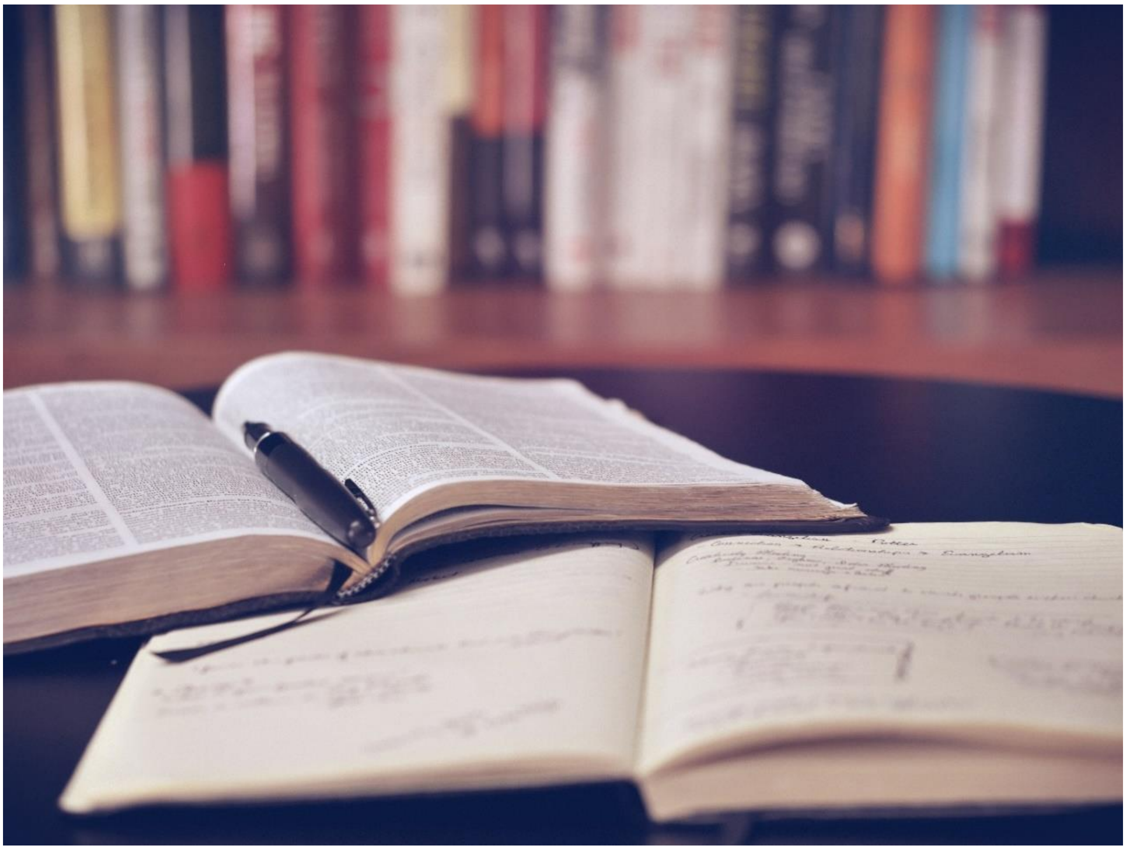

Drivers of intentions and drivers of actions: willingness to participate versus actual participation in fire management in Sardinia, Italy

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Abstract

Changing wildfire regimes coupled with budget cuts are spurring increased involvement of communities and citizens in fire management programs. Policy making faces the task of understanding citizens' willingness to participate and mobilizing will into actions. As there is no reason to expect that the same factors affect willingness to participate and actual participation in the same direction, policy making would require information both on citizens' preferences over management programs and on drivers and barriers to adoption. In this paper we compare data on preferences from a latent class Discrete Choice Experiment (DCE) with data on adoption of fire prevention and mitigation measures. The objective is to test if the same factors explain actual participation and willingness to participate in fire management programs. Results suggest that sufficient information for policy design cannot be gained exclusively from the DCE or the analysis of actual behavioural data as the sets of explanatory factors do not entirely overlap. However, two variables – knowledge of fire prescriptions and community's capacity – can be used to influence both the adoption of prevention and mitigation measures and citizens' willingness to participate in fire management. Policy makers can directly control these factors to nudge the public towards greater involvement in fire prevention and mitigation.

Keywords
Citizens' participation; Willingness to participate; Drivers of preparedness; Latent class discrete choice experiment

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1. Introduction

Predicted climate changes for the Mediterranean regions are expected to cause a significant shift in wildfire regimes in the next decades (Arca et al., 2010; FAO, 2013; FAO and Plan Bleu, 2018; Moriondo et al., 2006). The lengthening of the dry season, coupled with lower humidity and higher temperatures will increase the amount of combustible biomass and the risk of catastrophic wildfires (Flannigan et al., 2009; Liu et al., 2014, 2010; Seidl et al., 2014). Some evidences of these catastrophic scenarios have already appeared as documented by the huge increase of fires both in annual frequency and area burned (Pausas and Fernández-Muñoz, 2012; Salis et al., 2014).

Concurrent to these changes, the global financial crises and austerity measures in several countries have cut public expenditure in essential services, including firefighting (Ortiz et al., 2015). Shrinking public budgets and increased risk of wildfires require new strategies for fire prevention, mitigation and control. As it has the potential to both mitigate wildfire impact and save public money, there is a growing interest in promoting the active involvement of communities and citizens in adopting fire prevention and risk mitigation measures (Bihari and Ryan, 2012; McCaffrey, 2015; McGee, 2011; Morrison et al., 2014). For instance, Sardinia's regional government recognises the importance of citizens' involvement in the first page of its Firefighting Plan (Regione Autonoma della Sardegna, 2018). Sardinia (Italy) has a long history of wildfires that in the last 50 years have caused massive environmental damages and loss of human lives, properties and assets (Molina-Terrén et al., 2019). Over 90% of the fires are caused either accidentally or intentionally by humans (Salis et al., 2013). Hence, involving the community in fire prevention and mitigation could also address the social causes of wildfires and lead to a decrease in the number of events in the long term.

The challenge for policy makers and forest managers is two-fold: firstly, they need to understand if citizens are willing to participate in fire prevention programs and, secondly, they need to design policy instruments to mobilise will and intentions into actions. The literature on citizens' participation in fire prevention and mitigation usually focuses on either a) stated preferences over fire prevention programs, that overlooks actual barriers to and drivers of participation (e.g. Holmes et al., 2013), and b) factors, motives and constraints to actual participation (Canadas et al., 2016) that overlooks people's preferences for fire management programs. Any of these approaches provides sufficient information to policy design only when willingness to participate and actual participation are driven by the same factors in the same way. One can think of several reasons why this condition would not be met in reality: a legal framework enforcing participation even when citizens are not willingly adopting prevention measures; altruistic motives driving people's willingness to participate but lack of information preventing participation; fire prevention, mitigation and fighting seen as sole responsibility of experts and technicians, and so on. To tests if the same factors affect willingness to participate and actual participation, in this paper we assess citizens' willingness to participate in fire prevention and mitigation programs with the use of a discrete choice experiment (DCE) and contrast its results with a logit analysis of participation data on drivers of and barriers to adoption of fire prevention and mitigation measures. While comparisons of willingness to pay with actual payment are common (Carlsson and Martinsson, 2001; Kanya et al., 2019), as far as we know this is one of the first study to compare actual participation to stated intentions. The goal of the analysis is to provide information to guide policy design for fire prevention and mitigation in wildfire-prone regions like Sardinia.

The paper is structured as follows: Section 2 reviews the literature on stated preferences and wildfire prevention programs, and the drivers of adoption of fire prevention and mitigation measures; Section 3 contains the description of the methods used to elicit parameters for factors driving adoption and preferences; Section 4 presents the survey and data generation instrument, and Section 5, the estimation results. Section 6 concludes with a discussion about the findings.

2. Literature review

Two strands of research are relevant in the present investigation: a) the analysis of what motivates people to protect themselves and their assets against the risk of fires, and specifically the role of risk perception as driver of preparedness to catastrophic events; b) citizens' preferences over alternative fire management scenarios and the effects of attitudes, perceptions and subjective assessment of risk.

2.1 Drivers of preparedness

For some time, in the field of risk management and in other social sciences, the view that risk perception affects preparedness and adoption of preventive measures was popular (Sjöberg, 2002, 2000; Sjöberg et al., 2004). However, the relationship between risk perception and actual adoption is still uncertain. For some hazards, there is a significant correlation with neither intention nor actual adoption (Lindell and Whitney, 2000; Mileti and Fitzpatrick, 1992; Mulilis et al., 1990). For others, the correlation is significant and positive: higher risk perception is correlated with adoption and preparedness (McNeill et al., 2013; Ozdemir and Yilmaz, 2011). In other cases, risk perception seems to mediate the effect of other variables on adoption (Martin et al., 2007; Mozumder et al., 2008). In other contexts, risk perception is negatively correlated with adoption and preparedness (Wachinger et al., 2013).

This uncertainty has moved the focus of the research towards theories developed in the medical and behavioural field. For instance, the theory of "preparedness motivation" is now used to study individual behaviour in case of wildfires (Martin et al., 2007; Morrison et al., 2014). According to this theory, individuals can be motivated to adopt virtuous habits to avoid health risks and undesired social effects. In case of wildfires, for instance, the theory predicts that the probability of adopting preventive and mitigation measures depends on the subjective evaluation of: a) vulnerability of assets and personal health, b) risk severity, c) individual ability to avoid risks, and d) effectiveness of prevention and mitigation measures. On the other hand, the probability of not adopting prevention measures depends on a) the cost of adoption (e.g. the cost of creating a defensible space), b) the intrinsic benefits (e.g. the pleasure of having trees around the house), and c) the extrinsic benefits (e.g. the social approval of having trees around the house) (Floyd et al., 2000). Notwithstanding these theoretical refinements, the role of these elements in motivating individuals to adopt preventive and mitigation is still undefined (Martin et al., 2007).

Other recent developments related to preparedness and adoption of prevention measures are based on extending the models above to include individual and social characteristics as explanatory factors. There is indeed a growing consensus on the idea that private prevention and mitigation is the result of an adaptive and dynamic process born out of the integration of personal and social factors (Brenkert-Smith et al., 2012; Bushnell et al., 2007; Jóhannesdóttir and Gísladóttir, 2010). Individual-level characteristics have always had a central role in the theories of risk perception and preparedness. However, less attention has been paid to the complex network of social relations that affect individual decision processes (Gavilanes-Ruiz et al., 2009; Morrison et al., 2014; Sagala et al., 2009). On the one hand, we are witnessing a continuous refinement of individual-level factors, with models that include cognitive factors, such as the perceived responsibility for hazard prevention and mitigation and anxiety (Earle, 2010), as well as classical individual-level variables, like age, income, education level, etc. (Lindell and Perry, 2000; Lindell and Whitney, 2000; Paton et al., 2008; Wachinger et al., 2013). On the other hand, factors such as the place of residency, land uses, the availability of infrastructure, the collective experience of catastrophic events, and the role of public authorities, are increasingly employed to make explicit the relationship between individuals and society (Blanchi et al., 2006; Bushnell et al., 2007; Hess et al., 2008; Nicolosi and Corbett, 2018). Empirical research has also shown that the social capital plays an important role in the decision about adoption of preventive and mitigating measures. Even if an agreed-upon definition of social capital is still elusive, some researchers have applied this concept by breaking it into a series of measurable variables such as community trust, strength of social relations, community participation, social cohesion, and trust on authorities (Bihari and Ryan, 2012; Morrison et al., 2014; Paton, 2003; Wachinger et al., 2013). It appears, however, that it is not possible to overcome the inherent contradiction of conceptualising social capital as a community-level characteristic, while measuring it through the subjective perception or evaluation of social capital held by members of the community.

The list of individual and community-level characteristics used in explaining individual behaviour is fairly long. In the present exercise we are interested in: a) variables that clearly define groups or individual that could be the target of specific prevention policies (e.g. owners of assets at risk); or b) factors over which policy makers have a degree of control (e.g. information and education). Through policy design it would be then possible to nudge, provide incentives or stir individual behaviour towards better preparedness and wildfire prevention.

2.2 Stated preferences, attitudes and perceptions.

Stated preference methods are a set of techniques for generating individual-level data on people's preference over hypothetical choice scenarios or policies. Contingent Valuation (CV) and discrete choice experiment (DCE) are common stated preference approaches for evaluating willingness to pay (WTP) for environmental programs, including wildfire prevention and mitigation proposals (Gonzalez-Caban and Sanchez, 2017; Holmes et al., 2013; Loomis et al., 2009; Talberth et al., 2006). In the present study, we use a DCE to evaluate citizens' preferences over wildfire prevention programs.

Socio-economic characteristics and features of the choice scenarios are the standard explanatory variables used to estimate WTP for environmental programs (Ben-Akiva et al., 2019). However, accounting for heterogeneous perceptions and attitudes towards risk and environmental issues has been found to improve estimates of individual preferences over environmental management options. The heterogeneity issue has been investigated through different approaches. (Boxall and Adamowicz, 2002) set up a latent class choice experiments that explains preference heterogeneity with motivations towards wilderness recreation and perception of environmental quality. Recreationists are divided into four classes on the basis of motivation and perception scores calculated on 20 attitudinal questions. For each class a different set of utility parameters are estimated as function of attribute of choices. Boxall and Adamowicz conclude that their latent class model has identified an important source of preference heterogeneity and it was successfully incorporated by estimating a utility function for each latent class. Similarly, Beck et al. (2010) use a latent class approach to investigate influence of attitudes towards the environment on WTP for vehicle emissions. They found that the exact influence of environmental attitudes on willingness to pay is unclear even if they explain individual membership of latent classes. Hess and Beharry-Borg (2012), Morey et al. (2006)and Hess and Beharry-Borg (2012) also proposed using a latent class model but argue that attitudes are a function of latent preferences rather than the other way around as postulated by Boxall and Adamowicz. From this point of view, using responses to attitudinal questions as explanatory variables could lead to measurement errors and endogeneity bias. Hess and Beharry-Borg (2012) show that underlying attitudes helps to explain preference heterogeneity and define preference patterns across respondents. In contrast, Holmes et al. (2013) and Gonzalez-Caban and Sanchez (2017) use a latent class approach to investigate risk attitudes and preferences over wildfire protection programs but directly incorporate subjective evaluation of risk as explanatory variables in the utility function. They found that respondents living in subjectively-rated high risk areas have a higher WTP for public wildfire prevention programs than other respondents.

A third approach to incorporate attitudes and perceptions into WTP is based on postulates of Prospect Theory: gains and losses are defined relative to a reference point and losses are evaluated higher than corresponding gains (asymmetric preferences) (Kahneman and Tversky, 1979). DCE in environmental valuation often requires that researchers provide a description of the current state of a resource, or status quo condition (Bateman et al., 2002). Such descriptions are usually obtained from environmental baseline studies or expert opinions, and may differ from the people's perceptions of resource conditions. Hence, participants in DCE may factor in their own prior assessment of resource conditions in the valuation of an environmental program. Ignoring differences in the reference point or utility baseline may bias WTP estimates for environmental policies (Marsh et al., 2011). Ahtiainen et al. (2015), Glenk (2011) and Lanz et al. (2010) designed DCEs to evaluate the effect of individual-specific status quo and asymmetric preferences on WTP for environmental programs. They all found clear evidence of asymmetric responses to increase and decrease of levels of environmental attributes relative to the status quo, with the value of losses being larger than corresponding gains.

The role of respondents' prior belief or assessment has also been explored in relation to the final outcome of an environmental policy. Most environmental policies and programs have uncertain results, and these uncertainty has to be incorporated in WTP estimates (Lundhede et al., 2015). Rigby et al. (2010) and Mesa-Jurado et al. (2012), for instance, assess the willingness to pay for reducing uncertainty of water supply among Spanish farmers. Glenk and Colombo (2013) analyse alternative models of outcome-related risk and their impacts on willingness to pay for soil carbon sequestration programs. Dorner et al. (2019) elicit preferences for alternative water supplies by accounting for intrinsic water supply risks. These studies demonstrate that incorporating attributes that capture outcom uncertainty affects estimated preferences parameters. Lundhede et al. (2015) extend this literature by assessing the impact of a priori perceptions about uncertain environmental outcomes on WTP; they find a significant influence of priors on the estimated utility.

A related stream of stated preferences literature has assessed the effects of risk attitudes on individual choices in a variety of settings. In the field of wildfire management, Wibbenmeyer et al. (2013) and Hand et al. (2015) assess the role of risk preferences of wildfires managers through a DCE. They find that rather than being risk neutral, wildfire managers tend to be risk adverse; they over-allocate resources to low risk fire events and over-weigh actions with high probability of success. In contrast, Holmes et al. (2013) found that a large majority of citizens who participated in their DCE are risk seeking that is, a certain loss (paying to fund a wildfire prevention program) is valued higher than a probable one (losing a property following a wildfire).

In the present study, we design a DCE to understand citizens' preferences over wildfire prevention programs. Our DCE is based on the experiment design proposed by Gonzalez-Caban and Sanchez (2017) and Holmes et al. (2013) for the description of policy alternatives, but with additional attributes to match the definition of wildfire risk currently in use among wildfire managers (Scott et al., 2013). We aim at assessing preferences for citizens participation in wildfire programs other than just their WTP. As far as we know, this issue is largely unexplored in reference to wildfire management, with the only exception the study by Durán-Medraño et al. (2017). Furthermore, our design incorporate individual-specific status quo as in Ahtiainen et al. (2015), based on a set of questions designed to capture subjective wildfire risk probabilities, expected damages, and community's vulnerability and capacity.

3. Methods/Econometric models

This study consisted of two separate investigations on the same set of subjects. First, we assess what factors explain the adoption of fire prevention and mitigation measures. The explained construct is then a simple dichotomous variable equal to 1 whenever the respondent declares to have adopted one or more strategies to prevent or mitigate fire impact. We want to study how a set of predictor variables (that includes individual as well community-level factors) is related to the choice of adoption. Letting $Y=1$ denote the occurrence of adoption, and X the vector of predictors ($X_1, X_2, ..., X_k$), the conceptual problem can be analysed using a binary logistic regression model in which the probability that $Y=1$ given X is:

$$Prob(Y=1|X)=[1+\exp(\beta X)]^{-1} \tag{1}$$

where $X\beta$ is a linear combination of predictors: $\beta_0+\beta_1X_1+\beta_2X_2+...+\beta_kX_k$. The maximum likelihood method is used to estimate the regression parameters β (Harrell, 2015).

Second, we investigate individual preferences with regards to fire management programs starting from a random utility specification:

$$U_{ij}=\beta_{ij}X_{ij}+\epsilon_{ij} \quad i=1,..,N \quad j=1,..,J \tag{2}$$

It assumes that a person i gains a utility U_{ij} from choosing alternative j. X_j is a vector of observed attributes for alternative j and ϵ_{ij} is an unobserved stochastic variable. The vector of utility parameters β_{ij} is also unobserved and varies across the population on the basis of a distribution $g(.)$. Different estimation models derive from different assumption about the distribution $g(.)$. For each alternative, we specify a dichotomous variable y_{ij} that equal 1 when alternative i is chosen. The choice problem consists in selecting the alternative that provides the highest utility:

$$y_{ij} = \begin{cases} 1 & U_{ij}>U_{kj} \quad \forall i \neq k \\ 0 & \end{cases} \tag{3}$$

The probability of individual j choosing alternative i from the choice set N is:

$$P_j(i)=\frac{\exp(\mu\beta X_{ij})}{\sum_{i=1}^{N}\exp(\mu\beta X_{ij})} \tag{4}$$

where μ is a scale parameter that is typically set equal to 1. For the analysis reported in this paper, we assume that *g(.)* takes a discrete distribution[1]. The latent class model captures preference heterogeneity assuming individuals belong to an unknown finite number of classes (c) with preference parameters fixed within each class (Hess, 2014). The latent class model computes the choice probability for alternative i for each class as:

$$P_{j|c}(i)=\frac{\exp(\mu_c \beta_c X_i)}{\sum_{i=1}^{N} \exp(\mu_c \beta_c X_i)} \tag{5}$$

The probability that an individual belongs to class c is given by a membership function:

$$P_{(jc)}=\frac{\exp(\alpha \gamma_c Z_j)}{\sum_{c=1}^{C} \exp(\alpha \gamma_c Z_j)} \tag{6}$$

where γ_c is a scale parameter (set equal to 1), α is a set of constant used to compute class probabilities (Scarpa and Thiene, 2005) and Z_j is a vector of individual characteristics that affect the probability of belonging to class c. The identification of the model requires that parameters of the first class are normalized to zero (Sarrias and Daziano, 2017). The joint probability of an individual belonging to class c and choosing alternative i is simply the product of equations 5 and 6:

$$P_j(i)=\sum_{c=1}^{C} P_{jc} P_{j|c}(i) \tag{7}$$

In this specification, both the attributes of the alternative and the characteristics of each individual enter the model to explain the choice of an alternative.

4. Survey and DCE design

4.1 Survey background

Sardinia (Italy) is the second largest island in the Mediterranean Sea. It is the Italian region with the largest forest extension covering around 50% of the island or over 12.000 km^2 (Regione Autonoma della Sardegna, 2008). Sardinia has a long history of summer wildfires and like other Mediterranean regions it has experienced major shifts in fire regimes (Salis et al., 2014). In Sardinia fire prevention, mitigation and fighting is based on four cornerstones: a) a set of by-laws, annually revised and published by the Regional Government of Sardinia, dictates citizens' responsibilities and behavioural rules. Among other prescriptions, it contains rules for making fire breaks in private land adjacent to roads, creating defensible spaces around houses and farm buildings and the prohibition to light fires from the 1st of June to the 30th of October of every year. Exemptions requires a fire permit from the National Forestry Service (Regione Autonoma della Sardegna, 2020); b) a fire fighting force that coordinates personnel, vehicles, helicopters and aircrafts of the Regional Forestry Service, the National Forestry Service and the Civil Protection Department (Regione Autonoma della Sardegna, 2018); c) a system of fire breaks, water reservoirs and lookout posts spread all over the island for timely spotting and fast intervention and d) a daily fire forecast bulletin to inform citizens of the expected severity of fires in case of a fire event for each of the 26 areas covering the whole island, as identified in the Regional Fire Prevention Plan (Regione Autonoma della Sardegna, 2019).

Still, wildfires continue to cause large ecological and financial losses, accidents and fatalities (Molina-Terrén et al., 2019; Salis et al., 2013). As over 90% of forest fires in Sardinia are caused either accidentally or intentionally by humans (Salis et al., 2013) prevention and mitigation measures need to address the social, economic and behavioural causes to further reduce the number of fire events in the long term.

1 As discussed in the result section, the chosen model specification is based on AIC and BIC criteria.

4.2 Survey structure and sample

A survey on a sample of Sardinian residents was administered at the end of 2015 fire season. Trained personnel interviewed 328 randomly selected citizens at major shopping centres in the major towns of north Sardinia (see Table 1 for sample characteristics)[2]. The questionnaire consisted of 6 main sections. The first section contains a series of questions on the demographic characteristics of the respondents (such as age, income, education level, marital status). In the second section, a series of questions on respondent's usual place of residency are designed to test the hypothesis that people living in rural areas or at the margin of urban areas, having a closer relationship with the environment, and a higher probability of experiencing wildfire, would have preference parameters and a likelihood of adopting preventive measures that differ from urban residents. The third section is a series of questions regarding the individual knowledge, experience and information of the respondents. In particular, we are interested in assessing the individual knowledge of the local wildfire prevention rules and regulation. Further, this section contains a question regarding the ownership of assets at risk of wildfire damages. This data is used to elicit the relationship between information, knowledge, experience and ownership with preference parameters and preparedness. In the following section, respondents are asked to list the actions, if any, they adopt to prevent wildfires and mitigate their impact (see Table 2 for the list of prevention and mitigation measures). In case no action is undertaken, respondents are asked to list the reason for their inaction. The fifth section contains a set of questions on risk perception. Subjective wildfire risk is here modelled mirroring the USDA forest Service definition of risk (Scott et al., 2013) and is based on the theory of "preparedness motivation" (Martin et al., 2007; Morrison et al., 2014): respondents are asked to explicit the subjective probability of wildfires in their community, the expected damages (severity) according to different types of assets (infrastructure, houses, crops, farms, wilderness, industrial and commercial areas, etc.), and the subjective evaluation of the community's capacity (vulnerability) to prevent and fight fires. Each of these questions is structured as a 5 level Likert scale. Table 3 summarises the information collected through the survey and the variables used in the models estimation. Community-level variables are used as measures of social capital. For example, the share of workers occupied in the agricultural sector over the total workforce and the crime rates in the respondent's community are taken to be proxies of complex constructs such as social cohesion or community's trust.

4.3 DCE design

The sixth section of the questionnaire contains the question for the DCE. DCE (also known as choice modelling or choice experiment) is basically a structured method of data generation. It is used in several disciplines such as marketing, transportation, health care and environmental valuation (Hess and Daly, 2014). In our experiment, respondents are asked to select the preferred alternative from a choice set containing options A, B, and "No Choice". Options A and B are defined on the basis of five attributes. Three attributes take any of five discrete values (null, low, average, high and very high): the probability of wildfires in the respondent's community, the expected environmental damages (severity) of a fire events, the capability of the community to prevent and fight fires. A fourth dichotomous attribute is equal to 1 if the option envisages the active participation of private citizens in fire prevention and fighting, 0 otherwise. The cost of each option, i.e. the expenditure required to purchase the options in the choice set, is the fifth attribute. The attributes and their levels define the hypothetical outcomes of public fire prevention and mitigation programs and their cost to the community (see Table 4). By using a fractional factorial experimental design with blocking, the choice set is narrowed into 64 policy options that are compared with the "No Choice" option in a 3 set table, as in Figure 1. Each block contains 8 tables.

In assessing individual preferences over these hypothetical programs, the"No choice" option is individual-specific. This alternative, typically called status quo, reference or opt-out alternative, is included in the choice set to provide more realistic scenarios, avoid forced choices and provide welfare-consistent estimates (Bateman et al., 2002; Hanley et al., 2001). As in Ahtiainen et al. (2015), individual-specific status quo options are here based on respondents' risk perceptions: subjective probability of fires, expected severity and assessment of community's capacity. This design allows the estimation of preference parameters consistent with the predictions of prospect theory (Kahneman and Tversky, 1979): gains and losses are defined from a

2 Interviews took place at two shopping centres that attract visitors from the whole district. Hence the sample includes urban and rural residents.

reference point and losses are valued higher than corresponding gains. In the context of wildfire management it has indeed been shown that prospect theory better describes individual behaviour: Bartczak et al. (2015), Holmes et al. (2013) and Wibbenmeyer et al. (2013) find that wildfire managers' decisions are consistent with prospect theory; Bartczak et al. (2015) and Holmes et al. (2013) conclude that homeowners' strategy for avoiding wildfire damage is also consistent with prospect theory; Bartczak et al. (2015) show that the majority of their respondents exhibit prospect theory-consistent behaviour when taking decisions in both the financial and environmental domain.

5. Results

The result of the logistic regression explaining the adoption of fire prevention measures is presented in Table 5. The model is estimated using the **glm** function in R ("glm function | R Documentation," n.d.). The final specification of the model is selected on the basis of the AIC and pseudo R^2. The first noticeable result is the lack of significant community-level variables in the model. These variables were introduced to make explicit the connection between the individual and the community (such as the collective experience of wildfires) and as an indirect measurement for social capital (such as social cohesion measured by crime indexes - see Table 3). There appears that either these variables are not able to meaningfully capture these relations or that these social relations and connection have no role in explaining adoption of fire prevention strategies. On the other hand adoption seems to be driven mainly by individual characteristics and valuations.

Three individual-level variables have a positive and significant coefficient. Respondents who have had experience with fires, either in terms of property damage/loss or health effects, have a higher probability of adoption. As expected, they seem to be concerned with reducing the likelihood of another fire experience.

Knowledge of fire prescriptions and regulations also positively affects the probability of adoption. Either people are concerned about the possible fines and legal consequences of breaking the rules or the prescriptions increase their awareness of the fire danger and hence the need for prevention.

Sampled individuals who own a fruit orchard (vineyards, olive groves or similar) have also a higher likelihood of adoption while ownership of other assets does not affect fire prevention. One possible explanation is that some of these other assets (such as holiday houses or farms) could benefit from greater protection as fire fighting often focuses on protecting residential areas and buildings, and hence their owners do not judge necessary adopting private prevention measures. Furthermore, it is possible that some assets at risk have low economic values that does not justify yearly investment in fire prevention, as could be the case for woodlands and natural pasture.

Among the class of the risk perception variables, one factor helps to explain adoption. The subjective evaluation of the community's capacity for fire prevention is a five-levels categorical variable ("none" to "excellent", with "none" as the baseline) that has a positive significant coefficient for all but the "excellent" class. In other words, respondents who think their community has either negligible or first-rate fire prevention capacity are less likely to adopt private measures. In the first case, respondents may repute that any action on their part is useless as the community has not enough resources for fire prevention and fighting. In the second case, respondents may assume that no action on their part is necessary given the community's excellent system. The subjective probability of fires and the expected damage from wildfires have no effect on the probability of adoption.

Respondent's place of residency has more subtle effects on the probability of adoption. Firstly, it is not possible to conflate residency with wildfire risk as 10% of sampled urban residents own property at risk and 40% of sampled rural residents do not. Secondly, the *prima facie* evidence point to a distinction between residents in urban and rural areas: residents in small communities, hamlets and villages are more likely to adopt prevention strategies than residents in cities and towns. However, when interacting the categorical variables "residency" and "community's capacity", it emerges that rural residents who judge their community's capacity as "not good" or "good" have a lower probability of adoption than urban residents who expressed the same valuation, everything else being the same. It is not possible to identify a clear direction for the effects of the respondents' place of residency on the probability of adoption.

The econometric results of the DCE data are in Table 6. We present here the estimation results for a 2, 3 and 4-class models. Models are estimated using the **gmnl** function in R (Sarrias and Daziano, 2017). On the basis of the AIC and BIC statistics, the 3-class model is to be preferred[3]. Class 1 in the 3-class model represents about 2% of the sample and it is labeled "the Cost Conscious Class". It is made by respondents who are older than members of the other classes, live in urban areas, have experience of fire events and no knowledge of fire prescriptions. Members in this class do not make any trade-off between the fire probability and severity attributes; they are also indifferent to citizens participation in fire prevention and fighting; they prefer no change in the community capacity showing symmetric preferences over increase and decrease of the attribute; and finally, their cost attribute has a negative and significant parameter indicating they are concerned with the cost of fire programs. Contrary to what Holmes et al. (2013) found, respondents with experience of fire events are not making compensatory tradeoffs between the choice attributes but seem to adopt a simplification strategy based on the cost of each choice option.

81% of respondents are members of class 2 ("the Innovators"). The Status Quo variable for this class has a negative and significative sign indicating a preference for change from the current system of fire prevention and fighting; they are not anchored to the status quo. They also systematically trade-off attributes of the policy options, with the exception of the severity (environmental damage) attribute. They also show asymmetric preferences: increasing fire probability and decreasing community capacity would have a negative utility impact while a reduction in fire probability and a increase in community capacity would have positive effects on utility. Ahtiainen et al. (2015) report similar preference asymmetries for water quality attributes. Community participation is also positively valued. The cost attribute has, on the other hand, a negative and significative impact on utility.

Class 3 is labelled "the Active Class". It represents around 17% of the sample and its members have the same socio-economic characteristics as the Innovators class. They however have quite different preferences. Their major concern seems to be citizens' participation that they value positively. Also they do prefer a decrease in fire probability and an increase in community capacity. They ignore the cost and the severity attributes.

6. Discussion and Conclusions

Findings suggests theoretical and methodological reflections. A striking result is the paucity of explanatory variables identified in the logistic analysis. The theory on participation provides a plethora of plausible explanatory candidates but in the present analysis adoption of fire prevention measures is driven by a handful of factors. Rather than being a weakness of our model, we see it as a strength as it conveniently narrows down the number of factors that a policy maker should consider when attempting to influence public participation.

A second important result is that there is a set of core explanatory variables that are common for actual adoption and willingness to participate. Although our results indicate that information for policy design cannot be gained exclusively from the DCE or the analysis of actual behavioural data, they also identify two factors that policy makers can use to affect participation according to the public's preferences. The first is knowledge of fire prescriptions that has positive effects on both private adoption of prevention and mitigation measures and on the positive assessment of citizens' participation in fire prevention. This is the most important results of our analysis as policy makers and fire managers have a direct control over the public's knowledge of fire prescriptions. Fire prescriptions are widely publicized through the media, printed in booklet format, distributed in schools and public spaces. It appears that the information campaign on fire prevention and mitigation is proving successful: the informed public is more willing to participate in fire prevention and is actually adopting mitigation measures more often than the uninformed public. Hence this critical strategy should also characterise future policy design and implementation.

The second factor is the variable "community's capacity". In the analysis of actual adoption, this variable is the subjective evaluation of resources, competences, and abilities available to a community for fire prevention and fighting. It has a positive effects on the likelihood of adoption. In the DCE analysis, however, it measures the likely impacts of different fire management scenario on these resource, competences and abilities. Deterioration of community's capacity has significant negative welfare effects on the public. Policy makers have a degree of control over these variables: they can commit resources to maintain and improve

3 The 3-class models clearly outperforms the 2-class model both in term of AIC and BIC. The 4-class model has a larger BIC and smaller AIC than the 3-class model, but it also has a large parameter estimate for the Status Quo variable. Large parameter estimates are a symptom of weak identification (Sarrias and Daziano, 2017)

existing fire prevention and fighting capabilities; they can also influence public perception of their community's capacity and hence foster citizens' participation. Wildfire awareness and education campaign could focus on communicating both the resources committed and how they are performing.

Other important results point to the need for further research. In our analysis, the role of risk perception both in actual adoption and in willingness to participate is limited. We have here treated risk perception as a latent construct determined by the subjective assessments of fire probability, expected damages and community's capacity. As only the later seems to have significant influence both on actual participation and willingness to participate, further investigation on components of wildfire risk perception seems warranted.

The complex relation between place of residency and adoption of prevention measures also deserve further study. According to Nicolosi and Corbett (2018) place relations should to be positively related with public engagement. Arguably, one would expect that rural communities with stronger ties and connections have also better adoption rates than urban areas. However, our data suggests that "place relations" is the product of complex social and cultural processes – as shown by the interaction of the variable "residency" with the assessment of community's capacity - that shape the public response to wildfire risk in a less intelligible fashion. The challenge for researchers is to gain a better understanding of how these processes promote participation in order to provide policy making with more effective and refined tools.

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TABLES

Table 1. Selected statistics for sample and Sardinian population

	Sample	Sardinia
Male (%)	42	49
Female (%)	58	51
Resident in Urban Areas[(a)] (%)	55,4	54,1
Mean age	38	44,8
Mean income (€ X1000)	16,41	17,27
Education level [(b)]	49,4	51,4

[(a)] Urban areas= towns with more than 10.000 residents.

[(b)] Education level is the ratio between the population aged between 25 and 64 years with at best a college degree over the total population in the same age class.

Table 2. Definition of prevention and mitigation measures.

Strategy	Description
Fire breaks	Creation of fire breaks by ploughing, cutting or mulching
Defensible space by mulching	Creation of defensible space around buildings/properties by cutting and mulching
Defensible space by burning	Creation of defensible space around buildings/properties by cutting and burning
Water reservoirs	Positioning water reservoirs around the property
Escape routes	Identifying and maintain escape routes

Table 3. List of variables used in the estimation models.

Class	Variable	Type	Description
Individual socio-economic characteristics	Gender	Dichotomous	Respondent's gender: female=0, male=1
	Age	Discrete	Respondent's age
	Income level	Categorical	Respondent's income level measured through five classes
	Education level	Categorical	Education level measured through five classes
	Ownership of assets at risk	Dichotomous	Ownership of assets at risk. Assets are listed as: a) House; b) Holiday house; c) Farm; d) Grazing land; e) Vegetable fields; f) Fruit orchards (including olive groves and vineyards); g) Woodland; h) Cattle/sheep; i) Machinery
	Place of residency	Dichotomous	Urban residents live in towns of more than 10.000 inhabitants. Urban=0; Rural=1
Risk Perception	Knowledge of fire prescriptions	Dichotomous	Knowledge of fire prescriptions
	Experience of fire damages/events	Dichotomous	Experience of fire damages/events.
	Subjective probability	Categorical	Subjective probability of fire events in the respondent's community measured through a 5-point Likert scale (Highly unlikely, Unlikely, 50/50, Likely, Highly Likely)
	Subjective severity	Categorical	Subjective assessment of the severity of fire damages in case of fire events. Expected fire damages are measured on a 5-point Likert scale (None, Minimal, Average, Extensive, Catastrophic). The assessment is asked for different assets/sectors: a)Infrastructure; b) Agri businesses; c) Environment (forest, *maquis*, wild pasture) ; d) Cattle and sheep farms; e) Houses; f) People; g) Tourism and trade
	Subjective vulnerability	Categorical	Subjective evaluation of the community's capacity of fire prevention, mitigation and fighting. Measured on a 5-point Likert scale (None, Poor, Average, Good, Excellent)
Community-level variables	Occupation in agriculture		Share of workers occupied in the agricultural sector over total workforce in the respondent's community
	Property Crime rate		Rate of crimes against property in the respondent's community
	Violent crime rate		Rate of crimes against people in the respondent's community
	Last years fire events		Number of hectares burned during last fire seasion
	Last 15 years fire events		Number of hectares burned in the previous 15 years

Table 4. DCE attributes and levels.

Attribute	Description	Levels
Fire probability	Probability of a fire event in the respondent's municipality if the chosen fire program is implemented	Highly unlikely, Unlikely, 50/50, Likely, Highly Likely
Environmental damages	Severity of a fire event in the respondent's municipality if the chosen fire program is implemented	None, Minimal, Average, Extensive, Catastrophic
Community's capacity	Capacity of the community to prevent, mitigate and fight fires if the chosen fire program is implemented	None, Poor, Average, Good, Excellent
Citizen's participation	Active citizens' involvement in fire prevention and mitigation if the chosen fire management program is implemented	yes/no
Cost	Cost to taxpayers of the fire management program in euro	0, 20, 50, 100

Table 5. Logistic regression for adoption of prevention measures

	Parameters	P-values
Constant	-2.9542	0.00110 ***
Experience of fire damage (yes=1)	1.7374	0.05021 *
Knowledge of fire prescriptions (yes=1)	0.6552	0.01431 **
Ownnership of assets at risk (fruit orchards; yes=1)	2.7907	0.00000 ***
Residence (rural=1)	2.7962	0.01042 **
Community Capability (None=baseline)		
Community Capability (Not Good)	2.4780	0.00770 ***
Community Capability (Average)	1.6658	0.07492 *
Community Capability (Good)	2.5852	0.00601 ***
Community Capability (Excellent)	0.5602	0.72941
Residence (rural=1) * Community Capability (Not Good)	-3.5721	0.00267 ***
Residence (rural=1) * Community Capability (Average)	-1.1007	0.36081
Residence (rural=1) * Community Capability (Good)	-2.9027	0.01566 **
Residence (rural=1) * Community Capability (Excellent)	-3.2268	0.11856
AIC	376.48	
McFadden's pseudo R^2	0,228	
Number of observations	328	

*Variables are significant at the ***1%, **5%, *10% level*

Table 6. Latent class (LC) model estimates of preference parameters.

	2 -class model		3 -class model			4 -class model			
	Class 1	Class 2	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 4
	Parameters [(a)]		Parameters [(a)]			Parameters [(a)]			
Status Quo	0.8284 ***	-2.2567 ***	0.4427	-3.1486 ***	0.3521	0.4418	-10.2210 **	-2.7837 ***	0.3895 *
	0.0008	*0.0000*	*0.5867*	*0.0000*	*0.1338*	*0.5794*	*0.0133*	*0.0000*	*0.0982*
Fire probability (Inc)	-0.3688 **	-0.1574 ***	-1.8627	-0.1830 ***	-0.0960	-1.8580	-0.8394	-0.1180 **	-0.1064
	0.0136	*0.0009*	*0.1680*	*0.0004*	*0.3708*	*0.1608*	*0.2071*	*0.0339*	*0.3365*
Fire Probability (Dec)	-0.0711	0.1189 **	-0.0400	0.1012 *	0.1678 *	-0.0482	2.1652 **	0.0459	0.1789 *
	0.5549	*0.0213*	*0.8851*	*0.0788*	*0.0968*	*0.8591*	*0.0105*	*0.4629*	*0.0827*
Environmental Damages (Inc)	-0.0039	-0.0140	-0.0101	-0.0456	0.0605	-0.0176	-1.2983 *	0.0915	-0.0014
	0.9866	*0.8532*	*0.9890*	*0.5860*	*0.7300*	*0.9807*	*0.0682*	*0.3346*	*0.9945*
Environmental Damages (Dec)	-0.1045	0.0440	-0.2682	0.0495	-0.0428	-0.2526	-1.0745 ***	0.1179 **	-0.0638
	0.2406	*0.2479*	*0.4269*	*0.2436*	*0.5945*	*0.4579*	*0.0023*	*0.0189*	*0.4438*
Community Capacity (Inc)	-0.0313	0.1085 ***	-0.7169 *	0.0965 **	0.1581 *	-0.7118 *	2.4973 ***	-0.0012	0.1911 *
	0.7749	*0.0066*	*0.0922*	*0.0346*	*0.0751*	*0.0952*	*0.0031*	*0.9816*	*0.0341*
Community Capacity (Dec)	-0.3419 *	-0.2238 ***	-1.0284 *	-0.2713 ***	-0.0214	-1.0276 *	-1.3367 **	-0.2269 **	-0.0130
	0.0647	*0.0004*	*0.0949*	*0.0000*	*0.8790*	*0.0829*	*0.0310*	*0.0027*	*0.9285*
Citizens' Participation	0.6124 ***	0.3529 ***	0.6343	0.3173 ***	0.7533 ***	0.6629	2.2245 ***	0.2709 **	0.8130 ***
	0.0000	*0.0007*	*0.1787*	*0.0001*	*0.0000*	*0.1471*	*0.0008*	*0.0026*	*0.0003*
Cost	-0.0073 ***	-0.0022 ***	-0.0614 **	-0.0025 ***	-0.0016	-0.0614 *	-0.0382 **	-0.0018 *	-0.0015
	0.0063	*0.0054*	*0.0170*	*0.0046*	*0.4491*	*0.0115*	*0.0021*	*0.0588*	*0.4993*
Covariates explaining latent class membership									
Constant		2.1203 ***		3.5334 ***	1.9234 ***		2.2703 ***	3.2629 ***	1.8698 ***
		0.0000		*0.0000*	*0.0000*		*0.0000*	*0.0000*	*0.0000*
Age		-0.0320 ***		-0.0500 ***	-0.0351 ***		-0.0575 ***	-0.0489 ***	-0.0334 ***
		0.0000		*0.0000*	*0.0000*		*0.0000*	*0.0000*	*0.0000*
Income		0.2682 ***		0.0841	-0.0958		-0.0271	0.1089	-0.1158
		0.0001		*0.3199*	*0.3480*		*0.8497*	*0.2021*	*0.2635*
Experience of fire damage		-0.4587 **		-1.0672 ***	-0.9349 ***		-6.7039	-0.8867 ***	-1.0139 ***
		0.0246		*0.0000*	*0.0021*		*0.2585*	*0.0008*	*0.0013*
Residence (urban=0)		0.3275 ***		0.4751 ***	0.4531 ***		0.5496 **	0.4702 ***	0.4340 **
		0.0017		*0.0013*	*0.0076*		*0.0118*	*0.0016*	*0.0113*
Knowledge of fire prescriptions		0.1236		0.4305 ***	0.6604 ***		0.0537	0.4858 ***	0.6347 ***
		0.2604		*0.0065*	*0.0003*		*0.8081*	*0.0023*	*0.0006*
Gender (male=0)		-0.1029		-0.1624	-0.2413		-0.7183 ***	-0.0843	-0.3013 *
		0.3123		*0.2637*	*0.1539*		*0.0016*	*0.5637*	*0.0774*
Class probability	0.11	0.890	0.02	0.81	0.16	0.02	0.23	0.60	0.15
Log Likelihood	-2323,3		-2289.60			-2229.00			
AIC	4696,664		4601,16			4571.947			
BIC	4843,475		4841,987			4906.677			
McFadden's pseudo R^2	0,1626		0,1856			0,196			
Number of observations	2624		2624			2624			

*Variables are significant at the ***1%, **5%, *10% level*

[(a)] *P-values in italics*