International Journal of Disaster Risk Reduction 68 (2022) 102696

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Homeowners willingness to pay to reduce wildfire risk in wildland urban interface areas: Implications for targeting financial incentives

José J. Sánchez [a,*], Thomas P. Holmes [b], John Loomis [c], Armando González-Cabán [a]

[a] USDA Forest Service, Pacific Southwest Research Station, 4955 Canyon Crest Drive, Riverside, CA, 92507, USA
[b] USDA Forest Service, Southern Research Station, USA
[c] Department of Agricultural and Resource Economics, Colorado State University, USA

ARTICLE INFO

Keywords:
Choice experiment
Fuel reduction programs
Latent class model
Mail survey
Risk perception
Stated preference

ABSTRACT

This study estimated homeowner's willingness to pay for public and private fuel reduction programs in wildland urban interface areas using a choice experiment implemented in California. A multinomial logit (MNL) model was estimated and indicated that homeowners living in subjectively perceived high-risk areas would pay for new wildfire risk mitigation programs. This suggests the importance of risk perceptions in adoption of risk mitigation behavior. Prior research has indicated that demographic factors influence risk perceptions. Therefore, the heterogeneity of homeowner preferences regarding wildfire risk perceptions and mitigation behavior, not explicitly revealed in the basic MNL model, was investigated using Latent Class (LC) and Random Parameter Latent Class (RPLC) models. Results from the LC model indicated that homeowners with lower income/education levels are more likely to ignore risk factors in making wildfire mitigation decisions, and generally prefer the status quo to paying the costs of new wildfire risk mitigation programs. Similar results were found in the RPLC model, except for gender is no longer significant. These results suggest that many low income/education level homeowners in the study area will require accessible and persuasive information on wildfire risk as well as significant financial incentives to undertake private wildfire risk mitigation efforts on their property and to support broader public efforts to protect communities. In contrast, many higher income/education households are more sensitive to risk factors when making wildfire mitigation decisions and would pay a substantial amount for public and private programs, making the existing cost share approach for these types of households workable.

1. Introduction

Population growth in wildfire prone areas of the wildland-urban interface (WUI) is an emerging worldwide problem, and the ability to build resilient social-ecological systems will require focused efforts within human communities [44]. Within the United States, amenity migration during the past two decades has placed many residents of the United States in WUI areas that are at high risk of wildfires [53]. This is particularly evident in California, the most populous state in the USA. Similarly, researchers have recently begun identifying populations that are especially vulnerable to wildfire risk (i.e. less able to mitigate or recover from wildfire events) in

* Corresponding author.
E-mail address: jose.sanchez2@usda.gov (J.J. Sánchez).

https://doi.org/10.1016/j.ijdrr.2021.102696
Received 12 May 2021; Received in revised form 19 November 2021; Accepted 21 November 2021
Available online 27 November 2021
2212-4209/Published by Elsevier Ltd.

attempts to assure that wildfire mitigation programs are equitable as well as efficient [20,47]. A recent nationwide study found that nearly 10% of households living in places with high wildfire risk are also categorized as socially vulnerable [68]. Furthermore, Davies et al. [13] found that wildfire vulnerability is spread unequally across race and ethnicity.

To reduce wildfire risk, the USDA Forest Service (FS), state forestry agencies and local counties have offered cost-share programs to private homeowners and communities to conduct wildfire risk reduction actions, such as fuel reduction. Specifically, reducing flammable vegetation around individual houses and thinning out vegetation in the landscape in the surrounding neighborhood. Fuel reduction efforts on public and private lands are costly and funding limitations make it important for the FS and State Forestry agencies to understand the benefits of wildfire risk reduction programs when justifying budget requests to their respective legislatures.

To obtain the wildfire risk reductions agencies often require cost sharing. For example, in California, the Plumas County Fire Safe Council [51] requires community projects of at least 100 acres and landowners are required to match 25% of the total project cost. But the willingness and ability to participate in cost sharing requires members of the community to: (a) accurately perceive they are at fire risk, which can be a challenge as accurately interpreting risk information provided by agencies can be cognitively difficult, especially for those without higher education levels; (b) have the income that makes it possible for them to pay the cost share. Taken together, it is plausible that some communities with a majority of members with low education and income levels may not be willing or able to participate in cost share programs. Therefore, fire management agencies may have to pay the full cost of the fuel treatments.

From a conceptual standpoint, economists have recognized that vulnerable populations are less able to invest in wildfire risk mitigation and may depend more heavily on federal disaster assistance to help them recover from wildfire events [29]. However, very little empirical work has been conducted to test the hypothesis that vulnerable populations do not invest in wildfire risk mitigation activities. Collins [12] integrated a household survey with an in-field property hazard assessment and found that vulnerable groups were associated with lower levels of fire mitigation activities. There are a few studies on the role of income and education on the willingness to pay for fuel reduction programs using the choice experiment method, however, there are a few continent valuation studies in California and Florida [36,37,65]. González-Cabán and Sánchez [21] do use a choice experiment survey to investigate minority homeowner willingness to pay (WTP) for wildfire mitigation in Florida. González-Cabán and Sánchez [21] found that low income minority homeowners need assistance to participate in fire mitigation programs, while higher income minority households are willing to invest in public programs. However, results from González-Cabán and Sánchez [21] study cannot be generalized to California as they focus on two minority homeowner groups (i.e., Hispanics and African-American), while our study focus on the general California population.

The purpose of this current research is to use the choice experiment method to ascertain California homeowners' WTP to reduce the risk of wildfires in and around their residences and communities. A key element in this analysis is to provide a test of the hypothesis that lower income homeowners and levels of educational attainment are less likely to invest in wildfire risk mitigation in the future. We choose California because there are active fuel reduction programs. Furthermore, the experience of large and repeated wildfires suggests that residents living in the WUI are familiar with wildfire risk from forests.

In recent years there has been a concerted effort to inform homeowners of wildfire risk in order to persuade them to be more involved in reducing wildfire risk on their own private property. Furthermore, programs promoting fire-adapted communities have been created to help reduce wildfire risk in fire prone areas. These programs are developed by Fire Adapted Communities Coalition [16] and National Fire Protection Association [46]. FACC [16] define fire-adapted communities as "knowledgeable, engaged communities where actions of residents and agencies in relation to infrastructure, buildings, landscaping and the surrounding ecosystem lessen the need for extensive protection actions and enable the communities to safely accept fire as part of the surrounding landscape."

Stidham et al. [59] has compared the policy mechanism that six communities used to encourage community-level defensible space efforts. There are four policy tools being used in the communities. One of those tools is providing financial incentives to homeowners. In Oregon these authors found that up to $500 per household, has been successful in motivating people to participate in fuel reduction programs [59]. Other tools include capacity-building, persuasion, and authority. The community in the study area with a formal program was administered by the county with collaboration and support of local, state, and federal agencies, while the other communities relied on HOA and community members with collaboration with state agencies [59].

One approach to understanding the factors that motivate people and communities to participate in wildfire mitigation programs is based on understanding social context. For example, Paveglio et al. [49] developed a conceptual approach for identifying community archetypes and developed case studies that address how different archetypes influence strategies for wildfire mitigation, planning, and adaptation. They found that social factors such as local communication networks, community identity, and distrust of government are important factors influencing the development of community responses to wildfire risk. Furthermore, Paveglio et al. [48] found a positive relationship between income and risk, suggesting that higher income communities are correlated with higher overall risk to wildfire exposure. In contrast to a community-based approach for understanding wildfire risk reduction behavior, our study focuses attention on the influence of individual homeowner characteristics that may influence homeowners willingness to pay for fuel reduction.

The paper proceeds as follows: first we review the literature concerning household WTP for wildfire risk-reducing vegetation management programs and activities. This is followed by presentation of the choice experiment survey design, which investigated homeowner preferences for private and public wildfire risk reduction activities, and the survey mode used for data collection. Then the econometric models used for data analysis are described, followed by presentation of the econometric results and estimates of WTP for wildfire risk reduction activities surrounding homes and throughout broader forest landscapes. Finally, we present our conclusions.

2. Review of the literature: household WTP for fuel reduction

Here we present a brief summary of the stated preference literature that investigates household WTP for vegetation management activities that are designed to reduce wildfire risks. In general, stated preference methods can be broadly partitioned into contingent valuation method (CVM) surveys and choice experiment (CE) surveys. CVM surveys are used to estimate amounts that households would pay for holistic risk mitigating programs in which all wildfire risk factors are combined into a single summary measure such as the probability of a structure being destroyed (e.g. Ref. [18], or the total acreages burned by wildfires across a geographical area (e.g., Ref. [38]. CE surveys are used to estimate amounts that households would pay for attributes of risk mitigating programs such as the probability that a wildfire damages a structure and the dollar value of that damage (e.g. Ref. [27], thereby allowing estimation of WTP for multiple programs with different levels of attributes. Most studies of WTP for wildfire risk mitigation have used the CVM approach and have been applied to state and county wildfire risk reduction projects in California, Florida, and Montana [38], Michigan [18] and Colorado [32,45,65]. In these studies, the hypothetical wildfire risk reduction projects all involved mechanical thinning and prescribed burning of the forests in the county where the survey respondents resided. The WTP estimates for fire mitigation programs varied as a function of income [45,65] and by ethnicity [38]. The Fried et al. [18] CVM survey found median WTP of $24 ($37) to $75 ($116) per household per year for undertaking a public risk reduction action and $200 ($311) to $500 ($777) for actions on the respondent's property.[1] The CVM surveys of Loomis and González-Cabán [38] and Walker et al. [65] used a referendum format where households voted in favor of or against paying specific amounts for a county fuel reduction program. Loomis and González-Cabán's [38] CVM studies reported mean WTP per household for prescribed burning for California, Florida, and Montana at $460 ($547), $392 ($466), and $323 ($384), respectively. The mean WTP per household for mechanical fuel reduction treatments in these three states was $510 ($606), $239 (284), and $189 ($225), respectively. All three studies reported in Loomis and González-Cabán [38] specified a public program that would reduce the number of acres burned and the number of houses that would be destroyed. Meldrum et al. [45] found similar WTP estimates of $460 ($547) to $480 ($570) for vegetation reduction programs in southwest Colorado.

Furthermore, a few studies have been conducted in Europe that assess preferences towards fire prevention programs using CE. For example, Varela et al. [63] studied societal preferences for forest fire suppression programs in Málaga, Spain and found support for programs that reduce fire. Similarly, Slovenia residents support physical removal of excessive fuel, but without the use of prescribed fires [25,40]. More recently, Alló and Loureiro [1] found a significant WTP for wildfire prevention programs by Spanish households, although there was no difference in WTP for programs among residents of perceived high-risk areas relative to residents living in other areas. They refer to this phenomenon as a "risk paradox" (*sensu* [64], a subject addressed in our empirical analysis.

Standard economic approaches to decision making under risk are typically based upon expected utility theory (EUT). These model formulations suggest that homeowners will make investments in wildfire risk-averting activities in amounts that equal or exceed the actuarial value (probability of loss x loss amount) of potential damages from wildfires. The purchase of homeowner insurance, however, decreases the incentive for investments in risk-averting activities, thereby creating a "moral hazard" for insurance companies and inducing under-investment in public and private wildfire risk mitigation programs [29]. A CE survey implemented across communities in varying wildfire risk zones in Florida found that, on average, homeowner WTP for risk mitigation activities was generally much less than reductions in expected value loss. However, WTP was nearly equivalent to reductions in expected value loss for respondents having personal experience with wildfires who lived in subjectively perceived high-risk zones [27]. The authors argued that these results are consistent with prospect theory (PT) [31], a form of non-expected utility theory, in which people generally give too much weight to a certain loss (e.g., out-of-pocket vegetation treatment cost expenditures) relative to an uncertain and low-risk loss (e.g., potential fire damage).

These departures from EUT have been found to occur in European countries as well. Specifically, surveys of the general public in Poland regarding wildfire risks concluded that: "our results indicate that the assumption that EUT underpins respondent choices in stated preference surveys involving risky environmental goods may be misplaced … (and) it is reasonable to conclude that PT is indeed a better behavioral descriptor at least in the context of forest wildfires in Poland" [3]: 308). Evidence that even decision-makers rely upon non-expected utility decision rules was found in a study of fire managers' decision-making regarding wildfire expenditure allocation [67]. Given the growing interest in understanding the influence of risk perceptions on investments in wildfire risk mitigation activities, the CE survey used here allows us to estimate properties of risk-loss-cost trade-offs. Thus, one of the contributions of our analysis to the literature is to investigate these trade-offs in groups with different subjective risk perceptions and socioeconomic characteristics, particularly income and education.

3. Choice experiment survey design

An approach to understand the financial and other constraints facing households when they determine whether to engage in firewise fuel reduction on their own property and whether to support costly community wide fuel reduction efforts is using stated preference methods. Stated preference methods (e.g., contingent valuation, choice experiments) have widely been accepted as an appropriate valuation tool in the scientific community. Currently there are over 10,000 studies using contingent valuation method [24]. However, stated preference methods are controversial and receive criticism for generating inconsistent and unreliable estimates [14] and for their accuracy reflecting nonmarket values [25,42]. Based on our results below of having consistent negative cost coefficient estimates demonstrates internal validity, that is as costs for fire mitigation programs increases, support for the programs decreases. Studies have assessed the validity and reliability of contingent valuation method [9,34,50,66]. Moreover, Johnston et al.

[1] All of the WTP estimates in this section are first reported as nominal from the original article, and in parentheses in $2020 dollars to enhance comparison.

[30] provides best-practice recommendations for stated preference studies based in the accumulation body of peer-reviewed literature. Johnston et al. [30] provides 23 recommendations.

Accordingly, some of the recommendations we included in our study are: 1) clearly presenting status quo condition, the mechanism of change, and the change to be valued; 2) focus groups and pretesting; 3) developed an efficient experiment design; 4) payment vehicle selected was realistic, credible, and familiar; 5) survey protocol was reviewed by Office of Management and Budget; 6) reporting estimates of central tendency and dispersion; and 7) analysis should include the simplest and most parsimonious models and well as more-complex models.

The CE study we report in this paper used a survey previously developed and applied to homeowners in Florida [27]. Our study adapts this prior survey to California, and implements the survey during the beginning of 2015. The application of this survey instrument to homeowners in a state that has experienced massive loss of life and property from wildfires[2] during the past decade permits us to estimate risk-loss-cost tradeoffs while also identifying demographic characteristics of respondents that explain what social groups are more/less likely to undertake or pay for implementing fuel reduction around their homes and in their neighborhood. Although the Holmes et al. [27] found that homeowner's with previous experience with wildfires (either having experienced health effects or travel disruption) had greater WTP for wildfire risk mitigation activities, those characteristics are not discoverable in generally available data. This study differs from the prior study by seeking to identify demographic characteristics of respondents with greater/lesser WTP for investments in wildfire risk mitigation. Previous research has shown that wildfire prevention education efforts regarding the occurrence of certain types of wildfires (such as those caused by debris burning) are effective in reducing wildfire occurrence in Florida [52]. This result was found to be especially strong for media reports. We recommend that future research efforts explore the effectiveness of alternative wildfire risk mitigation outreach efforts, especially in low income/education communities.

The survey portrays potential monetary damages to respondents' homes in terms of expected losses (based upon risk and monetary damages) under alternative public and private wildfire risk mitigation scenarios. To orient respondents to these types of scenarios, the survey begins by introducing the idea that flammable vegetation throughout neighborhoods and surrounding homes increases the risk of home loss and a series of questions are asked to prompt homeowners to think about the vegetation where they live. These descriptions are provided in Fig. 1.

To help survey respondents develop an intuitive understanding of probability concepts for use in the hypothetical choice scenarios and questions, wildfire risk was characterized using a spatial "chance grid" illustrating the probability of a home being damaged by a wildfire (Fig. 2) and a risk ladder (Fig. 3), positioning wildfire risk relative to other ordinary risk factors (such as having a heart attack for a person over 35 years of age). The risk data for Figs. 2 and 3 were developed based on the available data at the time the survey was developed (2014), e.g. our relative incidence of heart attacks is within the range of heart attack data at the time of the survey (2012). The recent wildfires in California in the last three years due to drought would have raised respondents' perception of wildfire risk. However, as a long term average and one that portrayed the *relative risk* of wildfires compared to heart attacks and a road accidents is probably reasonable. As described below, the risk levels were varied across respondents in the survey inorder to estimate a coefficient on risk across the sample.

Both of these risk communication devices have been used in past surveys as a way of conveying to respondents relative and absolute risks [58,21,27,33,35].

The survey also collected information on individual characteristics, including respondent's age, gender, household income, educational attainment, and race/ethnicity.

Then, following Figs. 1–3, a series of questions are asked regarding what activities, if any, homeowners have undertaken in the past or intend to undertake in the future to mitigate wildfire risk, and whether they consider their landscape setting to be one of low, moderate, or high wildfire risk. These activities labelled "Wildfire Prevention Activities" and were tied back to Fig. 1. Specifically, whether they "Have Done" or "Would Do" the following activities: trim lower branches of trees, remove trees and flammable plants, remove branches hanging over houses.

Similar to Holmes et al. [27]; this survey uses three attributes to construct choice alternatives: (1) *risk (%)* of the respondents house being damaged by wildfires in the next 10 years (this attribute varied over five levels, from 1% to 5%, where 5% was the baseline risk and respondents were told this percent was associated with no new investments in wildfire protection programs)[3]; (2) monetary damage (*loss*) to respondents' property from a wildfire (dollar amounts varied over 10 levels that ranged from $10,000 to $100,000, where $100,000 was the baseline loss and respondents were told this was the monetary amount of damage associated with no new investments in wildfire protection programs); and (3) one-time per decade lump sum *cost* to the household for the ten year program (the *cost* of the programs varied over 10 levels ranging from $25 to $1500 for the public program and 9 levels from $50 to $1500 for the private program).[4] These variables were organized into three alternatives (a public program, a private program, and the status quo "do nothing additional") based upon an efficient fractional factorial design using Ngene software [54]. Note that the "do nothing additional" alternative establishes a baseline having zero cost with homes facing 5% risk and $100,000 property damage. Table 1 presents an example of one of the three choice sets presented in the survey.

We assume that people living in areas that have a higher risk of damage from wildfires would be more concerned about wildfire

[2] Nine of the 10 largest fire in California history have occurred within the past decade [66] and the 2018 Camp fire was deadliest in California history with 85 deaths and destroying 18,805 structures [67].

[3] We use *italics* to denote variables used in the empirical analysis.

[4] To help respondents think about trade-offs between program costs and expected losses, information on the *expected ten year loss = risk x loss* was included in the choice set.

High Fire Risk Landscaping

High Fire Risk Landscaping: Wildfire experts in California have determined that your home is at a **high risk** of being damaged by wildfire if most of the following are present around your home and in your neighborhood:
- A thick bed of pine needles on the ground (this carries fire across the ground)
- A continuous layer of highly flammable shrubs over 3 feet tall such as hedges (fire climbs into the trees)
- Vines and small trees underneath taller trees (fire climbs into to the trees)
- Several (6 or more) trees within 30 feet of your house, and a few trees (1-5) touching or extending over your home (trees can carry fire to the roof)
- Dense vegetation blocking the view of your home from the street
- Dense, difficult to walk through areas of forest within ½ mile of your home

Medium Fire Risk Landscaping

Medium Fire Risk Landscaping: Your home would be at a **medium risk** of being damaged by a wildfire if most of the following characteristics are present:
- Unmowed or tall grass, weeds or small shrubs, and fine bark as mulch
- A few (1-5) highly flammable shrubs over 3 feet tall
- No vines or small trees underneath taller trees
- 1 to 5 trees within 30 feet of your house; none touch the house or over the roof
- A partial view of your home from the street
- Easy to walk through areas of forest within ½ mile of your home

Low Fire Risk Landscaping

Low Fire Risk Landscaping: Your home would be at a **low risk** of being damaged by wildfire if most of the following characteristics are present:
- Mowed lawn, bare ground, pavement or gravel, chunky bark used for mulch
- No highly flammable shrubs over 3 feet tall
- No vines or small trees underneath larger trees
- Trees within 30 feet of your house should not touch each other or touch the house
- A clear view of your home from the street
- Easy to see through areas of forest or brush within ½ mile of your home

Fig. 1. Fire risk descriptions used in survey.

protection programs. Therefore, a stratified sample of California households was collected in 2015 and was primarily focused on obtaining responses from households living in areas considered to be at meaningful risk of wildfires. Specifically, using wildfire risk maps provided by the state of California (Fig. 4; [6], for each homeowner randomly selected from a moderate wildfire risk zone, two homeowners were randomly drawn from a high wildfire risk zone, and three homeowners were randomly drawn from zones rated as having very high wildfire risk. Fig. 4 also shows the zip codes in which surveys were completed.

This procedure resulted in a sample with more than half of the responses being obtained from homeowners living in very high wildfire risk zones.[5] Survey data were obtained using random digit dialing, which included both landline and cell phone, of households followed by a mail survey (see supplementary material for complete survey) sent to single family homeowners providing an address during the phone call. A welcome letter was included with survey instrument, which contained purpose of study, expected time to complete survey, and contact information of study representative. A postcard reminder was sent to non-responders approximately 14 days from sending the survey. Out of 1488 deliverable surveys we obtained 388 useable surveys for a response rate of 26%. The highest response rate was found for homeowners in high risk areas, followed by very high, and then moderate risk had the lowest response rate.

4. Econometric models of choice experiment responses

Choice experiment surveys are designed to elicit individual's choices among two or more alternatives, consisting of varying levels of policy-relevant attributes. Thus CE surveys allow researchers to estimate economic values of various attributes and attribute bundles [28,61]. CE analysis is generally based upon the random utility maximization model in which utility is considered to be the sum of systematic (V_{nj}) and random (ε_{nj}) components:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \equiv \sum_{k=1}^{K} \beta_{nk} x_{njk} + \varepsilon_{nj} \tag{1}$$

where x_{njk} is a vector of K explanatory variables observed by the analyst for alternative j and respondent n, β_{nk} is a vector of preference

[5] Sampling distribution is 53% very high, 36% high, and 11% moderate risk.

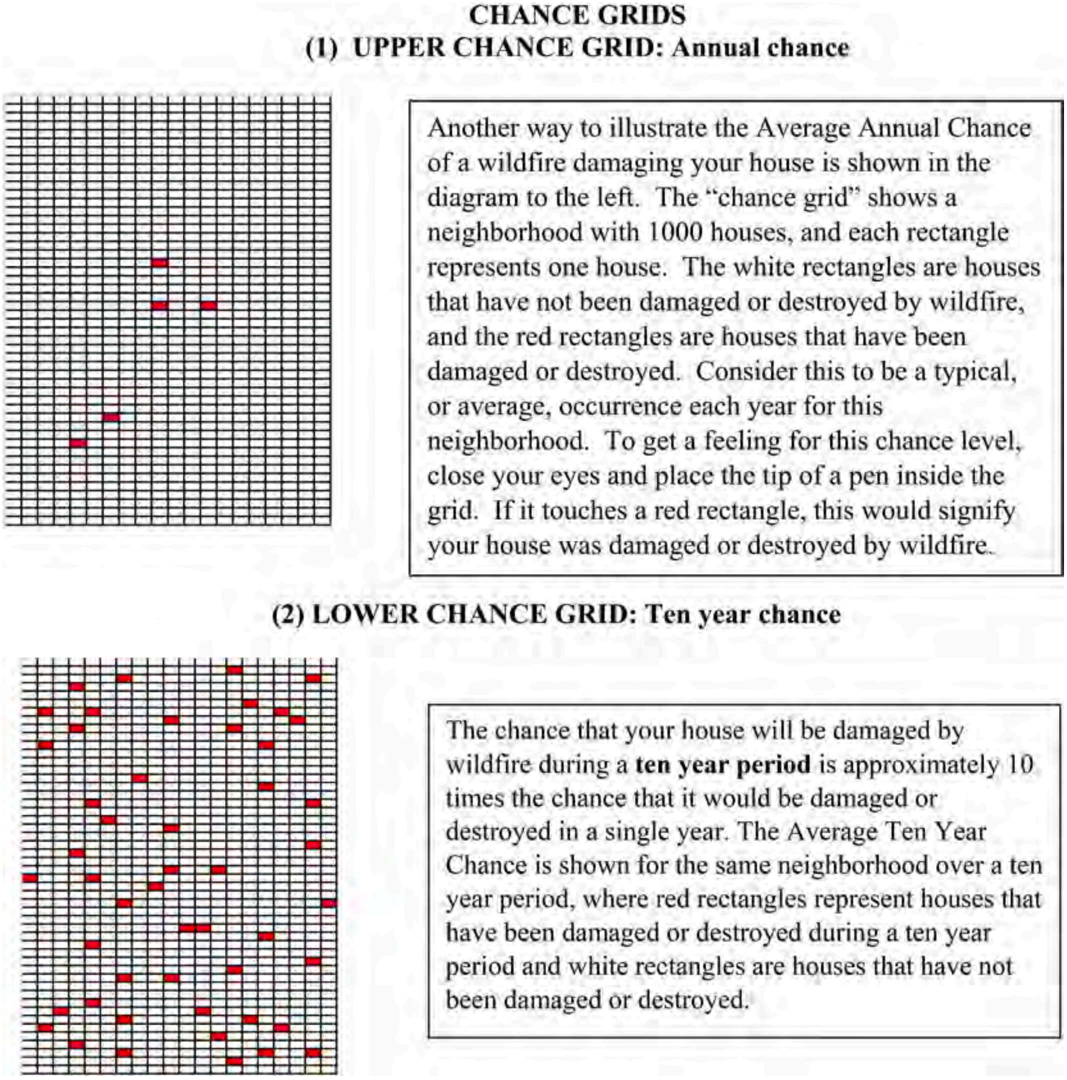

Fig. 2. Risk grids to convey relevant degree of wildfire risk to homeowner survey participants [27].

parameters, and ε_{nj} is an error term that reflects factors unobservable to the researcher and hence is treated as a stochastic variable.

To estimate the model in equation (1), assumptions are made about the specification of the utility function and distribution of the error terms. In particular, the standard multinomial logit model (MNL) is based on the idea that when faced with more than one alternative in a given choice set, respondents choose the alternative that maximizes their utility. In the MNL model, the unobserved stochastic variable is assumed to be independently and identically distributed (IID) following a type I extreme value distribution. The probability of individual n choosing alternative j from the set Θ is:

$$P_n(j) = \frac{\exp(\mu\beta x_{nj})}{\sum_{j\in\Theta}\exp(\mu\beta x_{nj})} \tag{2}$$

where μ is a scale parameter that is typically set equal to one.[6]

While the MNL model assumes that preference parameters are constant across the population of interest, and that the ratio of choice probabilities between any two alternatives is unaffected by other alternatives in the choice set, more advanced approaches relax these assumptions. Of the set of possible approaches that are available for relaxing these assumptions, the most basic approach is to interact sociodemographic characteristics of respondents with other variables of interest, such as wildfire mitigation program type. This model assumes that preference heterogeneity is distributed across specific, separable sociodemographic characteristics such as income or

[6] In all of the econometric models we present, the scale parameter is confounded with the β parameters of interest, and therefore we assume that its value is unity. In a single data set, the scale parameter cannot be recovered.

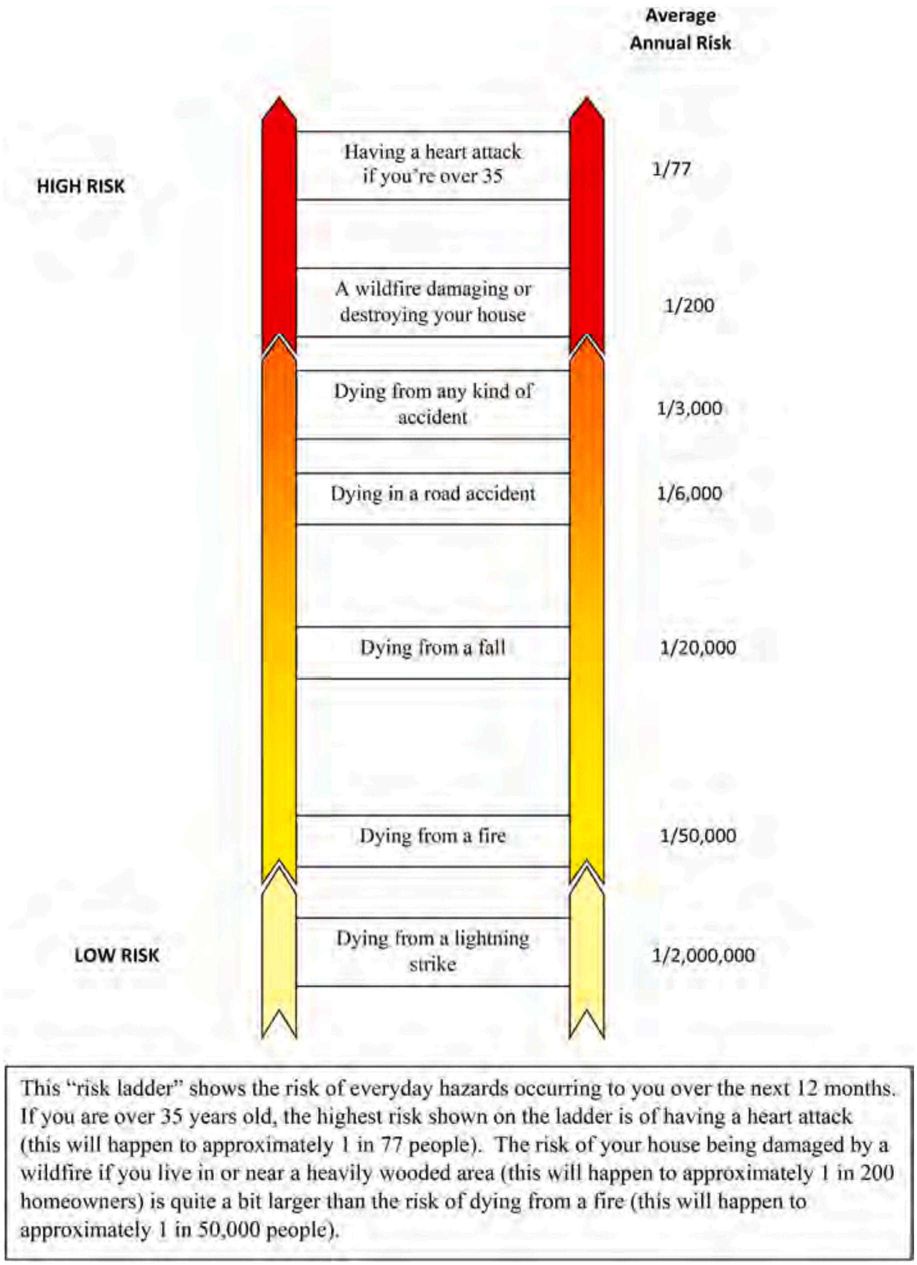

Fig. 3. Risk ladder used to illustrate to survey participants the risk of wildfires relative to other, ordinary events [27].

Table 1
Example of the choice set.

	Alternative 1	Alternative 2	Alternative 3
	Public Fire Prevention	Private Fire Prevention	Do nothing additional
Chance of your house being damaged in next 10 years	30 in 1000 (3%)	20 in 1000 (2%)	50 in 1000 (5%)
Damage to property	$20,000	$40,000	$100,000
Expected 10 year loss = Chance x damage	$600 during 10 years	$800 during 10 years	$5000 during 10 years
One-time cost to you for the ten-year program	$800	$1000	$0
I would choose: Please check one box	☐	☐	☐

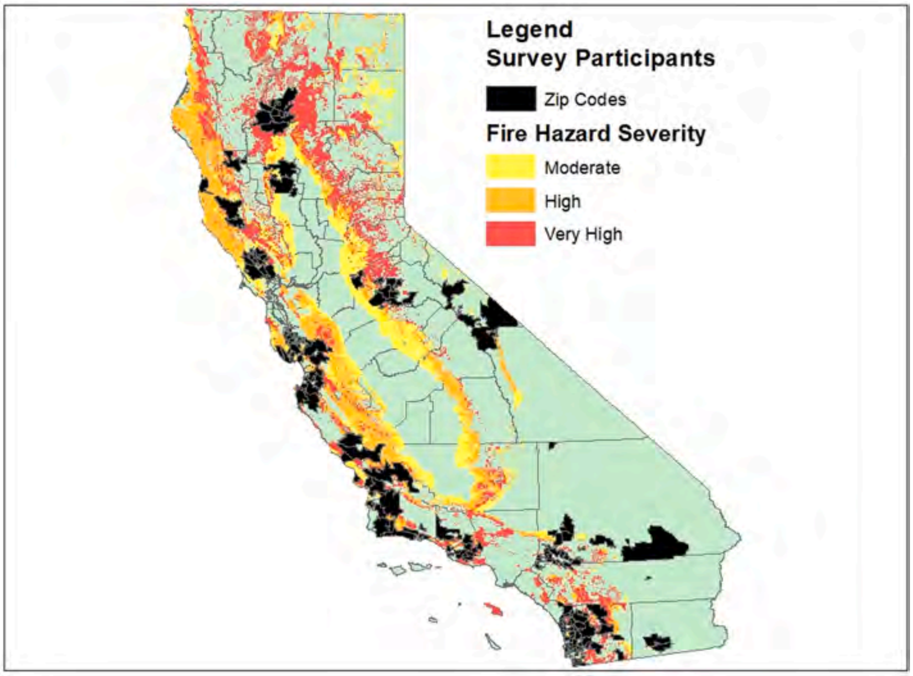

Fig. 4. California surveys completed by zip code and fire hazard severity zone map (data source: [6]. These categories define relative wildfire risks faced by homeowners in our sample.

gender. Given the purpose of this research to focus on the influence of education and income as determinants of willingness and ability to pay, we estimate this MNL model with demographic interaction terms.

A second, and alternative approach to modeling preference heterogeneity assumes that every individual has a unique preference, and that preferences for a sample of individuals can be described using continuous probability distributions across those individuals. The resulting random parameter/mixed logit model requires that the researcher specify the nature of the underlying distributions – such as uniform, triangular, or normal [26] – and a poor choice of the distributions in the model may lead to significant bias [19].

A third approach to modeling preference heterogeneity is to assume that preferences are distributed across multiple classes of individuals where membership in a class is a probabilistic function specified by a set of sociodemographic characteristics. The Latent Class (LC) model is used to capture preference heterogeneity for a finite number of classes by postulating the existence of C groups in the population with individual n belonging to group c, and that individuals within a group have homogeneous preferences [5,56]. The LC model can be extended by assuming that preferences are heterogeneous within sociodemographic classes [23,52]. The random parameter latent class (RPLC) model thus allows heterogeneity both within and between classes.

To provide some intuition as to how these models differ from the MNL model, without burdening the reader with extensive additional notation, we briefly describe the structure of the LC model. One issue with LC models is selecting the number of classes in the model as the determination of the number of classes is not part of the maximization problem [28]. To determine the number of classes, Greene [22] suggests adding groups until there are insignificant changes to log-likelihood or using one of the information criteria such as the Akaike information criterion (AIC) or Bayesian information criterion (BIC). The AIC and BIC are criterion for model selection. The estimation is based on the maximum likelihood estimate and the number of independent parameters; the procedure penalizes independent parameters to help reduce overfitting. AIC penalizes 2 times the number of parameters, while BIC penalizes using natural log of the number of observations times number of parameters. The selection of variables to be included in the group membership function should retain only relevant variables.

The utility parameters for each group and choice probabilities for alternative j for each group are:

$$\pi_{n|c}(j) = \frac{exp(\mu_c \beta_c X_{nj})}{\sum_{k \epsilon C} exp(\mu_c \beta_c X_{nk})} \tag{3}$$

where C is the set of all groups. The probability that individual n belongs to group c is assumed to be logistic:

$$\pi_{nc} = \frac{exp(\alpha \gamma_c Z_n)}{\sum_{c=1}^{C} exp(\alpha \gamma_c Z_n)} \tag{4}$$

where α is set equal to one (scale parameter), γ_c are specific class-related coefficients, and **Z** is a vector of individual's sociodemographic and other individual characteristics. Taking the product of equations (3) and (4), we can write the joint probability that an individual n belongs to group c and selects alternative j as:

$$\pi_n(j) = \sum_{c=1}^{C} \pi_{nc}\pi_{nj|c} \quad (5)$$

The parameter estimates are derived by the maximizing the log-likelihood function:

$$ln\ L = \sum_{i=1}^{I} ln\left[\sum_{c=1}^{C} \pi_{nc}\left(\prod_{j=1}^{J} (\pi_{nj|c})^{y_{nj}}\right)\right] \quad (6)$$

where y_{nj} equal 1 when individual n chooses alternative j and 0 otherwise.

In a CE, valuation of individual attributes is accomplished by dividing non-cost attribute coefficients by the absolute value of the cost coefficient [28]. The implicit prices (or the marginal WTP estimates) of the attributes is:

$$WTP = \frac{\beta_{attribute}}{|\beta_{Cost}|} \quad (7)$$

This value can be interpreted as the amount of money an individual is willing to sacrifice for a marginal change in the attribute. However, if the attribute is a dummy variable, indicating whether or not an attribute is present, then it is not possible to speak of a marginal change. In this case, the ratio shown in equation (7) represents the amount of money a respondent is willing to pay to make an attribute available that would otherwise be unavailable. In our case, the numerator in equation (7) is the alternative specific constants representing the availability of a public or private wildfire mitigation program. When interactions terms are included in the model, the marginal WTP is extended as follows [28]:

$$WTP = \frac{\beta_{attribute} + \beta_{interaction} Z_n}{|\beta_{cost}|} \quad (8)$$

5. Results

Descriptive statistics for the demographic variables collected in the survey are reported in Table 2. It is important to note that 7% of homeowners in our survey subjectively perceived that they lived in a high risk area, even though more than 80% of our sample was drawn from areas objectively assessed as being at high or very high risk of wildfires. This may be due in part to the fact that many homeowners reported that they had already conducted fuel reduction activities on their property, thus reducing their risk, or it may also reflect a difference between objective and subjective estimates of homeowner risk. For example, this result is consistent with Chivers and Flores [11] who found that a majority of survey respondents did not fully understand the degree of flood risk in their study. The low risk perception among a group of homeowners living in a high fire risk environment is also consistent with the conclusions of decades of research by psychologist Paul Slovic [57] that people understate the risks of familiar hazards (like wildfires in our case). This causes experts' rating of risk to be higher than the public's rating of risk [60]. Nonetheless, discrepancies between estimates of objective and subjective wildfire risk is a topic worthy of future research consideration.

We find that homeowners participating in the survey are predominantly *white* (88%), have an average *age* of 65, most are *college* graduates (69% have at least a Bachelor's degree or higher), and average household *income* is about $80,000. To understand how representative our sample is of California homeowners, we collected U.S. Census data of owner-occupied housing units in California. Overall, U.S. Census data show that California owner-occupied housing residents are white (57%), have a median age of 60, are less educated than our sample (43% have at least a Bachelor's degree), but have higher income (median household income is $87,000) than our sample [62]. As our sample indicates, California homeowners living in areas that wildfire professionals consider at greater wildfire risk are generally older, have lower household income, and are more highly educated than typical California homeowners. The demographic heterogeneity represented in our sample suggests that wildfire risk mitigation policies and programs should not be grounded solely on typical homeowner characteristics, but also needs to recognize the constraints faced by atypical homeowners. It is important to point out that 83% of respondents have already undertaken at least one fuel reduction activity on their property and 53% would do at least one more in the future. These activities they have already undertaken might be hypothesized to influence their probability of selecting the baseline "status quo" in the "Do nothing additional" alternative as well as the Private Program—further fire risk reductions surrounding their house and hence their WTP for additional private fuel reduction around their house. To test these hypothesis, we performed a chi-square analysis of whether there is a dependence of between selecting the: (a) "Do nothing additional"—Alternative #3 versus doing firewise activities in the future; and (b) "Private Fire Prevention"—Alternative #2 and having done firewise activities already; the results indicate that there is independence between selecting Alternative #2 and having done fuel reduction activities. Likewise there is independence between expecting to do future fuel reduction activities and selecting the status quo (Alternative #3).[7]

The estimated models were specified to include the probability of a wildfire occurring during a subsequent 10-year period (*risk*), property damage (in terms of $) caused if a wildfire occurs (*loss*), and cost to implement a 10-year wildfire risk reduction program (*cost*). To test whether the "risk paradox" [1] is evidenced in our data, we created an interaction term relating the perception of living

[7] Results are available from the senior author.

Table 2
Descriptive statistics of homeowners in California (n = 388).

Variable	Description	Mean (std. dev.)
Concern	Respondent indicated they are very concerned with wildfires in California; if Yes = 1; else = 0	0.52 (0.50)
high risk	Respondent indicated that home is located in a high fire risk neighborhood; if Yes = 1; else = 0	0.07 (0.25)
age	Respondent's age (years)	64.6 (13.06)
income	Household annual income (dollars)	$79,500 (42,200)
college	College graduate (Bachelor's degree or higher); if Yes = 1; else = 0	0.69 (0.46)
female	Respondent's gender; if female = 1; else = 0	0.44 (0.50)
percent white	Race (selected White)	0.88 (0.33)
future mitigation	Respondent willing to do at least 1 (future) private wildfire mitigation activity on their property; if Yes = 1; else = 0	0.53 (0.50)
past mitigation	Respondent previously made changes to landscaping on their property; if Yes = 1; else = 0	0.83 (0.38)

in a high risk wildfire zone (*high risk)* with the public wildfire program ASC (*public pro*high risk)* and private program ASC (*private pro*high risk*). A positive, statistically significant parameter estimate on both of these interaction terms provides evidence that the risk paradox is not fully operative among respondents in our study area.

For the MNL model, the ASC variables were interacted with selected sociodemographic variables (i.e., income, gender, and college) to investigate potential sources of preference heterogeneity. Since race was positively correlated with income and education, we could not include race as a variable as it would lead to multicollinearity which both inflates the variances around the estimated coefficients but also reduces the ability of search algorithms from converging in the highly non-linear models estimated below. In this model, the coefficients for *cost* and *loss* variables were negative, as expected and in conformance with economic theory (Table 3).

That is, the higher the program cost and monetary loss associated with a specific program, the lower the propensity of homeowners to select those program options. One way to interpret these coefficients is to compute the "implicit value" of an attribute as the attribute coefficient divided by the (negative of the) coefficient on cost. In this case, the implicit value of reducing the loss is 0.006/ 0.001 = $6.00. As the loss values are in thousands of dollars, this computation indicates that, on average, homeowners are willing to pay $6.00 to reduce losses from wildfires by $1000. We note that this amount is remarkably similar to average national insurance rates

Table 3
Multinomial logit (MNL) with sociodemographic interactions model estimates of preference parameters for wildfire hazard mitigation programs (The dependent variable is the alternative selected in the choice questions).

Variable	Multinomial logit model
risk (%)	−0.012 (0.035)
loss ($1000)***	**−0.006** (0.002)
*cost ($)****	**−0.001** (0.0001)
*public program****	**0.847** (0.236)
*public pro. x high risk***	**1.952** (0.968)
*private program****	**−1.164** (0.255)
*private pro. x high risk****	**2.63** (0.942)
*female x public pro**	**0.296** (0.151)
female x public pro x high risk	−0.039 (0.776)
*female x private pro.***	**0.374** (0.165)
female x private pro. x high risk	−0.541 (0.762)
*college x public pro.****	**0.650** (0.169)
college x public pro. x high risk	0.560 (0.792)
*college x private pro.****	**0.746** (0.191)
college x private pro. x high risk	0.314 (0.759)
*income x public pro.****	**0.006** (0.002)
*income x public pro. x high risk**	**−0.016** (0.009)
*income x private pro.****	**0.006** (0.002)
income x private pro. x high risk	−0.0148 (0.009)
n[a]	1164
McFadden pseudo R^2	0.102
Log Likelihood/AIC/BIC	−1136.27/2310.5/2406.7

Note: standard errors in parentheses.
***, **, * indicates significance at the 0.01, 0.05, and 0.10 alpha levels.
[a] There are 388 usable surveys, however each respondent had 3 choice set presented to them. Therefore, there is a total of 1164 observations in the econometric model.

of $5.91 per $1000 of home value as reported by Bankrate [2]. Although the coefficients on *cost* and *loss* were statistically significant at alpha level 0.01, the *risk* coefficient was not statistically significant in this model specification. However, the parameter estimate on *risk* had the anticipated (negative) sign, and the lack of focus on this variable may represent an editing/simplifying phase of decision-making inherent to PT [31]. This result is similar to results reported in Holmes et al. [27] for the State of Florida. We note that the significant coefficients for program types indicate that, on average, respondents are willing to pay for public programs although they are reluctant to pay for private programs (respondents generally prefer the status quo or will need to be compensated to participate in the private programs). Failure to identify possible heterogeneity of homeowner preferences might lead public officials to falsely conclude that there is no support for private wildfire risk reduction programs. The exception is homeowners living in subjectively perceived high-risk areas would consistently be willing to pay for new private and public wildfire risk reduction programs. These results are consistent with the literature in finding a relationship between wildfire risk perceptions and willingness to participate in mitigation behavior [10,27,39,43], but differ from the study by Alló and Loureiro [1] who found evidence of a “risk paradox”. Furthermore, respondents that were female, possessed at least a bachelor’s degree and received higher levels of income would be willing to pay to participate in new private and public programs.

In addition to the MNL model with sociodemographic and program type interactions to capture preference heterogeneity, a LC model was used to estimate homeowners’ WTP for wildfire risk reduction programs (Table 5). The LC model specification is similar to the MNL interaction model except that, rather than assuming that the sociodemographic variables have separable effects on preferences, sociodemographic variables are now specified in membership functions that identify sets of personal characteristics that create preference heterogeneity. Specifically, the LC model membership function sought to explain which respondents had higher/lower WTP values for new public and private wildfire mitigation programs based upon risk perceptions as well as demographic characteristics, including gender, income and education. We focus on possible budget and information constraints as they appear to be important factors for participating in fire mitigation programs [10,21,39]. Furthermore, because previous research indicated that gender has a substantial influence on risk perceptions [17,55], this variable was also included in the model specification.

The number of classes included in the LC model is generally determined based on information criterion and robustness of different models. The AIC was used to determine the number of classes.[8] A 2-class model was selected as the most robust model. Table 4 presents the descriptive statistics for the two groups, so as to give the reader of a sense of the similarities and differences between the groups. Respondent’s group is predicted using a probability function based on the estimated LC model parameters. That is, respondent *n* is predicted to be a member of group 1 if probability of being in group 1 > 0.5, otherwise the respondent *n* will be a member of group 2.

To check the robustness of our results, we also analyzed the LC model after removing possible protest responses. In general, protest responses result from respondents rejecting one or more premises of a WTP survey format (such as the belief that homeowners should not need to pay for public programs beyond taxes already paid or that programs would not reduce wildfire risk). See Boyle [4] for a more in-depth discussion of protest responses. In our study, protest responses were characterized as situations in which respondents selected the status quo option for each of the 3 choice set questions. As removal of protest responses did not alter our conclusions, we only present results from the LC model including all observations (complete results are available from the senior author).

As can be seen, there are significant differences between Group 1 and Group 2 in terms of level of *concern* about wildfires, their perception of whether they live in an area of high fire risk, their household *income*, and percent with college degree. As a shorthand expression we will refer to Group 1 as low income/education and Group 2 as high income/education group. Note that while respondents in the low income/education group were more than twice as likely to report that they subjectively perceived that they lived in an area with a high risk of wildfire, they were significantly less likely to state that they were concerned about wildfire risk. However, it is worth pointing out in Table 4 the similarity of the two groups on future fuel and past reduction mitigation activities. These small differences are not statistically different.

Table 5 presents the results of the two class LC model.

Notice that the goodness of fit statistic (McFadden pseudo R^2) in the LC model (Table 5) is substantially greater than estimated for the MNL model (Table 3), increasing from about 0.10 in the MNL to 0.33 in the LC model. In the estimated LC model, about 42% of the respondents were associated with Group 1 (low income/education) and 58% with Group 2 (high income/education). Looking at the membership function in the lower half of Table 5, it can be seen that respondents with lower levels of educational attainment and income were more likely to have their preferences represented by the Group 1 coefficient estimates. Furthermore, the group descriptive statistics shows the differences between the two groups as well (Table 4).

Table 5 indicates respondents in Group 1 tended to ignore the risk attribute by itself when making choices. However, perceived risk was positive and statistically significant when interacted with the specific public or private fuel reduction programs. The positive sign on the interaction term as compared to the own public and private fuel reduction program by itself, suggests support for these two programs only among those Group 1 respondents who perceive they live in high risk areas. Nonetheless, Group 1 did have statistically significant coefficients, with the anticipated signs for *loss* and *cost*. However, the coefficient estimates indicate that respondents in this group, in general, have a negative preference for public and private wildfire risk mitigation programs. Only Group 1 respondents living in a subjectively perceived high-risk area have positive preferences for new private risk mitigation programs.

Respondents with higher levels of educational attainment and income are more likely to have preferences represented by Group 2 coefficient estimates. As can be seen, respondents in this group have statistically significant coefficient estimates, with the anticipated signs, for *risk*, *loss*, and *cost* – signifying that they focused on all of the program attributes describing expected losses and costs. This result is similar to results reported in Holmes et al. [27] for the State of Florida. Furthermore, high income/education group, as a

[8] The three-class and four-class models have lower AIC estimates than the two-class model. Other LC models are available upon request.

Table 4
Latent Class Model descriptive statistics of homeowners in California by group.

Variable	Two-class model	
	Group 1 Mean (standard dev)	Group 2 Mean (standard dev)
*concern****	0.44 (0.50)	0.58 (0.49)
*high risk***	0.10 (0.31)	0.04 (0.21)
Age	65.6 (13.38)	63.9 (12.81)
*income****	$72,300 (42,222)	$84,700 (41,500)
*college****	0.59 (0.49)	0.76 (0.43)
Female	0.40 (0.49)	0.47 (0.50)
future mitigation	0.49 (0.50)	0.56 (0.50)
past mitigation	0.84 (0.37)	0.82 (0.38)
Sample size (n)	163	225

Note: ** significantly different at alpha level 0.05; *** significantly different at alpha level 0.01.

Table 5
Latent class model estimates of homeowner preference parameters for wildfire hazard mitigation programs among survey respondents.

Variable	Two-class model[a]	
	Group 1	Group 2
risk (%)	0.162	−0.109**
	(0.128)	(0.044)
loss ($1000)	−0.018***	−0.010***
	(0.007)	(0.002)
cost ($)	−0.0025***	−0.0017***
	(0.0005)	(0.0002)
public pro.	−2.347***	2.940***
	(0.642)	(0.302)
*public pro.*hi risk*	2.056***	0.130
	(0.672)	(1.069)
private program	−3.427***	2.813***
	(0.671)	(0.313)
*private pro.*hi risk*	5.389***	−3.534
	(0.600)	(2.389)
Membership function		
constant	0.742***	–
	(0.283)	
income ($1000)	−0.005*	–
	(0.003)	
college	−0.704***	–
	(0.247)	
female	−0.376*	–
	(0.227)	
class membership probability	0.42	0.58
n	163	225
Total n	1164	
McFadden pseudo R^2	0.328	
Log Likelihood/AIC/BIC	−859.26/1754.5/1845.6	

Note: standard errors in parentheses. * indicates significance at the 0.10 alpha level, ** indicates significance at the 0.05 alpha level, *** indicates significance at the 0.01 alpha level.
[a] In the two-class model, Group 2 is the baseline.

whole, expressed preferences for conducting private and public wildfire risk mitigation, regardless of whether or not they lived in a subjectively perceived high-risk area. Although these results provide some evidence consistent with the "risk paradox" [1], they also might be explained by the relatively small number of responses from members of this group that consider they live in a high-risk area.

Additional models were estimated to investigate other possible sources of preference heterogeneity and understand whether the LC model did the best job of explaining the variation in respondent choices. In particular, we estimated a random parameter (RP) multinomial logit model with demographic interaction terms and a random parameter LC (RPLC) model (results are shown in the appendix).[9] Results from RP multinomial logit model (table 1A) shows that risk and loss are not significant, however the standard

[9] We included expected loss variable in models as suggested by reviewers. However, comparing model fits, models having *risk* and *loss* variables has a better model fit than model that include expected loss. Therefore, we don't present result in paper. These results are available from senior author.

deviation for both variables are very significant, suggesting that the variation in the preference for these two variables is very large relative to mean value estimates. Furthermore, both program types are significant at the 0.05 level for respondents subjectively perceived living in a high-risk area. The RPLC (appendix, table 2A) has similar results to the LC model, except that gender is no longer statistically significant in the membership function and the statistical significance of the parameter on income increases to the 0.05 level. To identify which model has the best statistical fit, the McFadden R^2 as well as information criteria (AIC and BIC) were used. Based on these criteria (see Table 6), results consistently demonstrate that the LC model has the best fit.

The WTP formula (equations (7) and (8)) was used to estimate one-time mean WTP for a 10-year wildfire risk reduction programs using the LC model (Table 7), (See tables 3A, 4A, and 5A in appendix for MNL, RP, and RPLC model WTP estimates). Equation (7) was used to estimate the mean WTP for low to moderate subjective risk, while equation (8) was used to estimate the high subjective risk mean WTP. Following Greene and Hensher [23]; only statistically significant parameter estimates were included in the WTP estimation. The high-risk and program interaction estimates are added to the program estimate due to their statistical significance for Group 1, in order to derive the high subjective risk mean WTP. However, for Group 2, WTP for the public/private and high public/private are the same due to the high-risk perception and program type being statistically insignificant.

The positive WTP estimates represent the lump sum monetary value homeowners would pay once each decade to support public or private programs to reduce risk and damage. In the cases where a negative WTP is estimated, these values represent amounts that homeowners would need to be compensated or subsidized to prefer a private or public risk reduction program to the status quo.

Homeowners in Group 1, who are more likely to represent households with lower levels of educational attainment and income, are generally found to have negative WTP values for wildfire risk mitigation programs. These results suggest that low income and education homeowners – living in areas the respondents consider low to moderate risk of experiencing wildfires will require financial incentives to participate in private or public wildfire risk mitigation programs. In particular, Group 1 homeowners living in what they perceive as low to moderate fire risk areas require about $950, on average, to support public programs, and about $1,390, on average, to engage in private programs that substantially reduce wildfire risk.

The WTP estimates are modified somewhat for Group 1 homeowners that subjectively perceive that they reside in high risk neighborhoods. These homeowners would need a financial incentive of about $120, on average, to prefer public wildfire risk mitigation programs over the status quo. However, this public WTP amount is not statistically different from zero at the 95% level, we have less confidence in suggesting whether or not Group 1 homeowners living in subjectively perceived high risk neighborhoods would be inclined to participate in future public wildfire risk mitigation activities under various financial incentive scenarios.

Group 1 households that live in what they perceive as high risk areas exhibit a modest WTP for private risk mitigation programs ($800/household, on average), an amount that is about one half what Group 2 households would pay. The substantially lower WTP of Group 1 households in this case, may be due to the significantly lower income between Group 1 and Group 2, thereby lowering their ability to pay.

In contrast to Group 1, households with higher levels of educational attainment and income (Group 2: high income/education) exhibit substantially greater WTP for public and private wildfire risk reduction programs. The one-time mean WTP for a 10-year public and private programs to help reduce wildfire risk and property damage are $1770 and $1,700, respectively (Table 7). We found no differences in WTP between homeowners in Group 2 that consider themselves to be living in high risk areas and those considering themselves to be living in low or moderate risk areas (similar to results reported in Ref. [1]. These results suggest that homeowners with higher levels of income and education - living in areas considered by California wildfire professionals to be at moderate, high, or very high risk of experiencing wildfires – support the idea of managing vegetation around their home and throughout their communities. As such, these communities may not require financial incentives to encourage this behavior, but perhaps only need to be nudged using tools such as information and capacity building. Thus high income/education Group 2, would very likely pay a reasonable cost share for fuels management programs as well.

There are similar patterns in the WTP estimates for the various models (Tables 3A–5A). In general, WTP estimates are always higher among homeowners that view themselves living in a high-risk area. Comparing the WTP estimates for LC model (Table 7) with the RPLC model (table 5A), there is a small difference in the WTP estimates, suggesting our values are robust.

Importantly, our WTP results from this 2015 survey are likely conservative as there has been a significant increase in large and deadly fires in California since 2018. A poll by University of California Berkeley found that 75% of California residents see wildfires as a "*much more serious threat than in the past*" [15]:1). This suggests that in a rapidly worsening environment of increasing frequency and severity of natural hazards it is important to for decisionmakers to periodically monitor public values associated with potential proactive responses to these natural hazards.

6. Summary and conclusions

Many WUI communities around the world are facing increasing risks to life and property posed by wildfires and are testing alternative approaches to reducing human impacts by encouraging individual and community risk mitigation activities [59]. Researchers have recently begun to empirically evaluate the degree to which wildfire risk mitigation programs address the needs of vulnerable populations [13,21,47,68] and there is a clear need for an expanded research program in this area. To be action oriented, pragmatic and forward-looking, such a program would build upon the insights gained to date from economic and social analyses. This

Table 6
Model comparisons.

Model	McFadden R^2	AIC	BIC
1. Multinomial Logit (w/interactions)	0.102	2310.5	2406.7
2. Random Parameter	0.237	1970.1	2015.6
3. Latent Class	***0.328***	***1754.5***	***1845.6***
4. Random Parameter LC	0.326	1767.3	1878.7

Table 7
Latent Class one-time each decade Mean WTP per homeowner for a ten year public and private wildfire risk reduction actions (2015 Dollars).

	Homeowners			
	Homeowners with Low to Moderate Subjective Risk		*Homeowners with High Subjective Risk*	
	Public	Private	Public	Private
low income/education				
Group 1 Mean WTP[a]:	-$950	-$1390	-$120	$800
(95% Confidence Interval)[b]	(-$1670, -$230)	(-$2270, -$510)	(-$810, $580)	($320, $1270)
high income/education				
Group 2: Mean WTP[a]	$1770	$1700	$1770	$1700
(95% Confidence Interval)[b]	($1370, $2180)	($1300, $2090)	($1370, $2180)	($1300, $2090)

[a] Applying equations (7) and (8) results in slight differences in WTP estimates due to rounding.
[b] Delta method was used to construct confidence intervals.

paper contributes to these efforts by econometrically identifying homeowners living in wildfire prone regions of California that may face constraints to participating in wildfire mitigation cost-share programs. Homeowners living in zones considered by California wildfire professionals as exhibiting moderate, high, or very high wildfire hazard severity are found to be older and more highly educated than California residents in general, and substantial demographic heterogeneity is exhibited in these communities. Understanding the financial and other constraints faced by the more vulnerable members of these communities can help fire mangers and community leaders develop fuel reduction projects that help reduce mitigate wildfire risks for all residents.

In order to better understand homeowner investments in individual and community risk mitigation, a CE was conducted to estimate homeowner WTP for risk mitigation programs that varied in the amount of wildfire risk, financial loss, and vegetation management cost. Using a LC econometric model that permits analysis of preference heterogeneity across the sample of respondents, it was found that homeowners with lower levels of income and education would generally require financial incentives of about $1000 and $1400 to participate in individual and community wildfire risk mitigation, respectively. Although experience with providing financial incentives to homeowners in Oregon, of up to $500 per household, has been shown to be successful in motivating people to act [59], our results suggest that these amounts might be inadequate to overcome the financial constraints faced by some low income/education populations in California.

The reliance on observable demographic characteristics such as income and education has an important advantage for the practical application of our results. Information on education and income are available down to the U.S. Census Tract Block level. Block level data is a relatively small area that is bounded by roads or streams, and could be as small as a city block in WUI areas. As such fire managers can determine which neighborhoods have high enough income and education that simply providing information on needed fuels reduction may generate private action and support for public efforts. These neighborhoods would likely participate even at modest cost share amounts. In contrast, neighborhoods with low incomes and education levels may require not only accessible information, but significant financial incentives to undertake private actions, and to support public efforts and using Census Block locational information the incentives can be targeted fairly precisely.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by the USDA Forest Service under Research Joint Venture Agreement 13-JV-11272131064 with Colorado State University. The authors would like to thank the editor and anonymous referees whose comments substantially improved this article. The authors gratefully acknowledge the many contributions of our colleague Dr. Armando González-Cabán who passed away before completion of manuscript.

Appendix

Table 1A
Random parameter multinomial logit model estimates of preference parameters for wildfire hazard mitigation programs with random parameters estimated for risk and loss variables (The dependent variable is the alternative selected in the choice questions).

Variable	Random Parameter Logit Model	
	mean	std. dev.
risk (%)	0.086 (0.075)	0.795*** (0.106)
loss ($1000)	−0.004 (0.004)	0.053*** (0.006)
cost ($)	−0.002*** (0.0002)	–
public program	−0.575 (0.438)	–
public pro. x high risk	3.682** (1.812)	–
private program	−0.943** (0.461)	–
private pro. x high risk	4.341** (1.97)	–
female x public pro.	0.265 (0.325)	–
female x public pro. x high risk	1.696 (1.644)	–
female x private pro.	0.348 (0.338)	–
female x private pro. x high risk	0.869 (1.708)	–
college x public pro.	1.160*** (0.383)	–
college x public pro. x high risk	−1.951 (1.574)	–
college x private pro.	1.146*** (0.393)	–
college x private pro. x high risk	−1.880 (1.674)	–
income x public pro.	0.012*** (0.004)	–
income x public pro. x high risk	−0.020 (0.017)	–
income x private pro.	0.011*** (0.004)	–
income x private pro. x high risk	−0.020 (0.018)	–
n[a]	1164	
McFadden R^2	0.251	
Log Likelihood/AIC/BIC	–958.03/1958.1/2064.3	

Note: standard errors in parentheses. ***, **, * indicates significance at the 0.01, 0.05, and 0.10 alpha levels.
[a] There are 388 usable surveys, however each respondent had 3 choice set presented to them. Therefore, there is a total of 1164 observations in the econometric model.

Table 2A
Random parameter latent class model estimates of homeowner preference parameters for wildfire hazard mitigation programs among survey respondents

Variable	Two-class model[a]			
	Group 1		Group 2	
	mean	std. dev.	mean	std. dev.
risk (%)	0.201 (0.148)	0.738×10^{-4} (31.909)	−0.103** (0.040)	0.0001 (11.245)
loss ($1000)	−0.015** (0.007)	0.325×10^{-5} (0.477)	−0.010*** (0.002)	0.004×10^{-2} (0.435)
cost ($)	−0.0023*** (0.001)		−0.0016*** (0.0001)	
public pro.	−2.199*** (0.538)		2.883*** (0.291)	

(*continued on next page*)

Table 2A (*continued*)

Variable	Two-class model[a]			
	Group 1		Group 2	
	mean	std. dev.	mean	std. dev.
*public pro.*hi risk*	−34.479		−0.042	
	(0.109×10^{16})		(0.861)	
private program	−3.284***		2.750***	
	(0.670)		(0.301)	
*private pro.*hi risk*	4.787***		−0.616	
	(0.583)		(0.901)	
Membership function				
constant	0.733**		–	
	(0.290)			
income ($1000)	−0.006**		–	
	(0.003)			
college	−0.733***		–	
	(0.255)			
female	−0.351		–	
	(0.229)			
class membership probability	0.40		0.60	
n[b]	1164			
McFadden pseudo R^2	0.326			
Log Likelihood/AIC/BIC	−861.67/1767.3/1878.7			

Note: standard errors in parentheses. ***, **, * indicates significance at the 0.01, 0.05, and 0.10 alpha levels.
[a] In the two-class model, Group 2 is the baseline.
[b] There are 388 usable surveys, however each respondent had 3 choice set presented to them. Therefore, there is a total of 1164 observations in the econometric model.

Table 3A
Multinomial logit one-time WTP per homeowner for a ten-year public and private wildfire risk reduction actions (2015 Dollars)

	Homeowners			
	Homeowners with *Low to Moderate Subjective Risk*		Homeowners with *High Subjective Risk*	
	Public	Private	Public	Private
	(95% Confidence Interval[b])			
Mean WTP[a]:	-$640	-$880	$840	$1110
(95% Confidence Interval) [b]	(-$1030, -$250)	(-$1320, -$440)	(-$580, $2250)	(-$260, $2480)

[a] Applying equations (7) and (8) results in slight differences in WTP estimates due to rounding.
[b] Delta method was used to construct confidence intervals.

Table 4A
Random parameter one-time WTP per homeowner for a ten-year public and private wildfire risk reduction actions (2015 Dollars)

	Homeowners			
	Homeowners with *Low to Moderate Subjective Risk*		Homeowners with *High Subjective Risk*	
	Public	Private	Public	Private
	(95% Confidence Interval[b])			
Mean WTP[a]:	$0	-$440	$1700	$1570
(95% Confidence Interval) [b]	($0, $0)	(-$870, $2)	($50, $3350)	(-$170, $3310)

[a] Applying equations (7) and (8) results in slight differences in WTP estimates due to rounding.
[b] Delta method was used to construct confidence intervals.

Table 5A
Random parameter latent class one-time WTP per homeowner for a ten-year public and private wildfire risk reduction actions (2015 Dollars)

	Homeowners			
	Homeowners with Low to Moderate Subjective Risk		*Homeowners with High Subjective Risk*	
	Public	Private	Public	Private
	(95% Confidence Interval[b])			
low income/education				
Group 1 Mean WTP[a]:	-$970	-$1450	-$970	$670
(95% Confidence Interval) [b]	(-$1645, -$300)	(-$2500, -$405)	(-$1645, $300)	($270, $1060)
high income/education				
Group 2 Mean WTP[a]:	$1770	$1690	$1770	$1690
(95% Confidence Interval) [b]	($1390, $2160)	($1320, $2060)	($1390, $2160)	($1320, $2060)

[a] Applying equations (7) and (8) results in slight differences in WTP estimates due to rounding.
[b] Delta method was used to construct confidence intervals.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2021.102696.

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