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Do any differences between perceived and professional wildfire risk influence the amount homeowners would pay for public and private fuel reduction?

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Wildfire risk has risen significantly due to climate change and the increase in housing development in the wildland urban interface (WUI), making household participation in fuel reduction crucial. However, homeowners' perceived wildfire risk may diverge from professionals' objective assessments. We use a choice experiment survey of Arizona homeowners in WUI areas to compare how willingness to pay (WTP) for public and private fuel reduction programs aligns with self-assessed versus professionally determined wildfire risk. Results show that while homeowners' WTP for fuel reduction is positively correlated with their perceived risk, those living in objectively higher-risk areas—according to professional assessments—are not willing to pay more for either program. This disparity in risk assessment and WTP for fuel reduction may undermine residents' engagement in mitigation efforts and program effectiveness. We highlight three strategies to better align homeowners' and professionals' risk assessments that may help to narrow this gap.

Keywords: choice experiment; fuel treatments; risk perception; wildland urban interface; WUI

1. Introduction

Climate change and population growth in wildfire prone areas of the Wildland-Urban Interface (WUI) is a problem that is expected to continue. In 2022, the USA had over 68,900 fires that burned over 8 million acres (NIFC [National Interagency Fire Center] 2024). According to the NIFC, the last 10 years has seen federal wildfires cost over $2 billion to suppress 8 million acres of wildfires (NIFC 2024). Nearly half the US Forest Service (USFS) budget is now spent on fighting fires, leaving limited resources for the other half dozen multiple uses the agency is charged with managing on the National Forests. A similar situation is true for other federal multiple use agencies such as the Bureau of Land Management. The two other federal land management agencies, the National Park Service, and to a lesser extent the US Fish and Wildlife Service, face a similar challenge in some years.

Reducing the quantity of fuels through either thinning or prescribed burning are the "leading wildfire reduction strategies in the American West…" (Hjerpe *et al.*

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2024, 1). However, performing fuel treatments on public and private lands are expensive and the limited resources make it difficult to implement treatments in all the fire-prone landscape. For example, the costs for private homeowners to hire contractors to perform fuel reduction on their own property is about $1,000 an acre (Meldrum *et al.* 2014). There are millions of acres in need of fuel reduction treatments. However, in 2022 Congress doubled the amount of money to address the wildfire situation appropriating $5 billion dollars, primarily focused on projects to reduce forest fuels. This amount of funding represents more than double the historic spending from 2018 to 2020 (Wear, Wibbenmeyer, and Joiner 2024).

To help reduce the cost to homeowners and communities to reduce wildfire risk, the USFS, State Forestry agencies, and local counties have cost-sharing programs. However, in these programs, homeowners are typically required to contribute a portion of the project costs for fuel reduction activities. In our study area, the State of Arizona has a WUI grant program to reduce hazardous fuels. This program required a 50% match (Arizona State Forestry 2016). The match could be met by dollars spent by local groups as well as "in-kind" contributions of homeowners and family members on their own property or volunteer time in the community (Arizona State Forestry 2016). A USDA program called Community Wildfire Defense Grants (USDA 2023) requires a 25% match on fuel reduction project implementation. Eligible organizations include Homeowners' Associations (HOA's), communities and counties. Plumas County, California also has a 25% match for its Fire Safe program (Plumas County n.d.). For these local entities to meet the 25% to 50% match for such fuel reduction grants special HOA assessments or specific County property tax assessments are often involved.

Given the cost share being at least 25%, it is important for agencies to know the amount homeowners would pay for mechanical vegetation removal, such as thinning on homeowner's private land and public land, as well as how much they would pay for prescribed burning on community or nearby public lands. This information would be very useful for agencies to aid in determining which of these types of fuel reduction demonstration projects or grant priorities that the agencies should emphasize.

In this paper, we estimate homeowners' WTP for two types of fuel reduction programs: the public program and the private program in Arizona. In addition, this paper investigates two important underlying factors that often impede individual homeowner support for fuel reduction on their property and in their community: (1) whether highly publicized "mega fires" of the last decade have changed the disconnect between homeowners' perceived versus managers' objective wildfire risk found in past literature dating back to data collected by other authors, generally during the 2007–2013 time period; and (2) whether willingness to pay a cost share for fuel reduction projects are now equivalently related to both perceived and objective risk.

2. Literature review

Slovic (1987), who, along with co-authors, and other independent researchers have conducted numerous surveys asking the general public and experts to rank a wide variety of risk. Slovic (1987, 280) observes: "Whereas technologically sophisticated analysts employ risk assessments to evaluate hazards, the majority of citizens rely on intuitive risk judgements, typically called risk perceptions". This conclusion is echoed in an article 25 years later by Brenkert-Smith *et al.* (2013), who indicate that, in some cases, people lack access to the detailed information professionals have about specific risks, and may not have the analytical skills to assess how risks apply to their personal situation. Instead, they rely on heuristics, such as visible cues, neighbor input, and media coverage, often rationalizing the risk with beliefs like 'it won't happen to me'.

In Meldrum *et al.*'s (2015) study, homeowners who were given the same risk factors that professionals use still underestimated the wildfire risk to their properties compared to professionals, because, the authors' infer, the public may be weighing these elements differently in their assessments than the professionals do.[1]

Unlike Meldrum *et al.*'s (2015) very controlled experiment, in most cases, a likely source of some of the disparity is also that wildfire professionals use a detailed wildfire risk model framework based on factors such as historical weather, land-use patterns, vegetation density, topography, and suppression difficulty to assess wildfire risk (Sanborn 2013). Most households' wildfire risk perceptions are often based more on a subset of readily visible factors in proximity to their homes (Donovan, Champ, and Butry 2007). Wachinger *et al.* (2013) note that personal experience with a natural hazard and whether individuals trust information being provided by authorities and experts have the most impact on individual's risk perception. Taken as a whole, the literature seems to suggests that divergences between individual risk perception and objective risk estimates of experts are: (a) partially due to access to information on elements that professionals use their evaluation of a particular risk; (b) the weights given to each element; (c) substitution of individual's own or personal network of experience in place of professionals experience and/or data. This disconnect is not limited to wildfires, as the debates in the United States over the last decade concerning required immunization of students for enrollment in schools illustrates.

A competing hypothesis is that homeowners are well aware of the high risks of living in areas with high natural hazards, such as forests, flood-prone rivers or along the hurricane-prone coastlines, but the amenities gained are worth the risk. In these situations, such households make a rationale utility maximizing decision. However, their maximization of their private utility has often been conditioned on past experience that the state and federal government, e.g., taxpayers, will pay a substantial amount of the cost of preventing damage or responding to the damage. For example, mitigating some of the natural hazard by widening beaches by pumping sand onto the beach that was swept away in the last storm. When significant events such as wildfires or hurricanes occur, government agencies and the homeowners' insurance companies will aid in rebuilding after damaging events, e.g., helping pay to raise the elevation of the house. Given the increasing frequency and magnitude of wildfires and hurricanes, the subsidization by taxpayers and insurance companies of rebuilding in high hazard areas is becoming financially unsustainable.

Our model and results cannot *explicitly* test whether any disconnect uncovered between homeowners' perceived risk and objective risk is due to lack of information and/or analytical capability of the homeowner to assess the risk *versus* they know the risks as well as professionals but the risk is worth the amenity of living in the forests. However, our model and results provide insights into these two hypotheses. First, is whether households would not pay for the fuel reduction program, especially around their own home. Second, qualitative insights may be available in comments that they enjoy the privacy and shade trees in close proximity to their house provide.

Comparisons of objective and perceived risk measurements have primarily been investigated in *valuation studies* related to water quality (Artell, Ahtiainen, and Pouta 2013) and traffic noise (Baranzini, Schaerer, and Thalman 2010). Some studies show that people who perceive higher risks are more likely to participate in fuel reduction activities (e.g., Brenkert-Smith, Champ, and Flores 2012; Champ, Donovan, and Barth 2013; Sánchez *et al*. 2022; Talberth *et al*. 2006). However, it is uncertain whether their valuations are also sensitive to objective risks assessed by professionals.

Meldrum *et al*. (2015) does demonstrate disparities between professional and perceived wildfire risk rankings in a small area of Colorado, and their 2014 paper investigates WTP for fire risk reduction efforts. Our analysis tests these disparities in risk assessment and examines whether disparities in wildfire risk perception influence homeowners' WTP for wildfire prevention measures for an entire state, thus increasing the generalizability of the results. This knowledge has significant policy implications for funding allocations and the effectiveness of the programs.

Further, previous studies that have explored households' WTP for fuel reduction to mitigate wildfire risks, mostly rely on the contingent valuation method (CVM), and often do not estimate separate WTP for specific program features or use older CVM methods to elicit WTP. For example, Talberth *et al*. (2006) conducted a study, examining WTP for public and private fuel reduction programs in eastern New Mexico using an open-ended CVM format. However, open-ended CVM has limitations, including hypothetical and strategic biases (Boyle 2017; Mitchell and Carson 1989). The most thorough evaluation of household WTP for fuel was conducted by Meldrum *et al*. (2014) using dichotomous choice CVM. Dichotomous choice is a best practice CVM method. Their study is, however, limited to their small area of Colorado which is relatively fire prone, and focuses primarily on the homeowners' own property.

We contribute to the literature in four ways. First our state-wide analysis includes homeowners with greater variation in susceptibility to wildfire than the small geographic area in the Meldrum *et al*. (2014) study. This increases the generalizability of our results. Second, our study also goes beyond focusing on fuel reduction just on homeowners' property but includes an additional fuel reduction option: a community or HOA wide fuel reduction program in the county. Third, is that we use a choice experiment approach to valuation, which allows us to determine whether the valuation of these two different fuel reduction programs, one on homeowners' property and one community wide, have different values to survey respondents. Specifically, a choice experiment forces homeowners to make trade-offs between the two, and results in estimates in their valuation of each program capturing substitution effects. This recognizes the funding limitations associated with fuel reduction programs. Thus, we can assess the priorities of homeowners for cost sharing between these two different types of fuel reduction programs. Fourth, we evaluate whether the signs and significance of the choice experiment attribute coefficients and dollar values for the two types of fuel reduction programs align with homeowners' own perceived risk as well as managers' objective assessments.

3. Study methods

As mentioned above, we use a choice experiment method instead of contingent valuation to quantify household willingness to pay for fuel reductions. Choice experiments are historically referred to as conjoint in business literature (Louviere 1994). Choice experiments (CE) provide a respondent with 2–3 "action alternatives" that carry a cost, and usually a "no action" or "status quo" alternative that has no cost to the respondent.

Each alternative also displays the characteristics or attributes of each alternative. In our study of applied CE in Arizona, the salient attributes were percentage chance your house was damaged by a wildfire, dollar amount of the damage if the house was affected by a wildfire and one-time cost of the program to your household. The two action alternative fuel reduction programs were: a Public Program that thins out vegetation in the landscape in the surrounding neighborhood and community, and a Private Program that reduces flammable vegetation around individual houses. The definitions of the two program types were clearly stated in the survey to ensure respondents fully understood them before answering the choice questions. There was also a "do nothing additional" alternative. An example of one of our choice experiments is shown in Figure 1. The dollar values vary across the alternatives, and across the sample, to allow us to estimate the marginal value of the attributes, including the value of the Public Program and Private Program. More detail is provided in the next section on how the range of dollar amounts was chosen. The CE method also allows us to test whether the alternative selected in each choice set is statistically related to the homeowners' perceived risk as well as managers' professional objective risk. This standard choice experiment design does force the respondent in each choice set to select just one alternative. However, across the three choice sets (three variations on Figure 1) that the respondents must answer in each respondent's survey, differences in the levels of the attributes and the cost of each alternative may result in a respondent choosing the Public Program in one choice set, and the Private Program in another choice set.

4. Survey design

We conducted a CE in the state of Arizona. This state has a population of 7 million people. Contrary to the public perception of Arizona being solely desert, nearly half the population of Arizona live in areas of moderate to high or very high fire risk, and in some areas extreme fire risk (e.g., Prescott area, Globe). Since 2.5 million people live in the Phoenix-Tempe-Mesa metropolitan area, of the remaining 4.5 million, 3 million of them live in the WUI (FAC [Fire Adapted Communities] 2017). Nationwide, FEMA (Federal Emergency Management Agency) (2024) indicates that Arizona is the second only to California in the proportion of the state in the Relatively High (just one from the highest category) wildfire risk category.[2]

Before asking the valuation questions, we provided the respondent with an exercise and information to develop an intuitive understanding of probability concepts for use in the choice scenarios and questions. The spatial "chance grid", which illustrates the probability of a home being damaged by a wildfire, was used to characterize the homeowner's wildfire risk (Figure 2). To provide context for wildfire risk relative to other ordinary risk factors, such as dying in a road accident, we presented a commonly used risk ladder (Figure 3). These risk figures have been used in past surveys to convey to respondents absolute and relative risks (González-Cabán and Sánchez 2017; Holmes *et al*. 2013; Krupnick *et al*. 2002; Smith and Desvousges 1987).

Carson and Groves (2007) suggest that for quasi-public goods a choice experiment format where respondents trade-off the costs of alternative "packages of attributes" may be close to incentive compatible in terms of estimating the marginal values of each of the attributes. In our study, these attributes are risk reduction, damage to the house, and cost to the homeowner.

Q18.	Alternative #1a	Alternative #2a	Alternative #3
	Public Fire Prevention	Private Fire Prevention	Do nothing additional
Chance of your house being damaged in next 10 years	10 in 1,000 (1%)	40 in 1,000 (4%)	50 in 1,000 (5%)
Damage to property	$75,000	$50,000	$100,000
Expected 10 year loss = Chance x damage	$750 during 10 years	$2,000 during 10 years	$5,000 during 10 years
One time cost to you for the ten-year program	$200	$1,000	$0
I would choose: Please check one box	☐	☐	☐

Figure 1. Example choice set used in survey.

More formally, we model the utility of living in the WUI as a function:

$$U = f(\text{Expected Loss}, \text{ Income} - \text{Cost of the Program})$$

Where expected Loss is a function of two attributes in our choice model: (a) the probability of a wildfire, described as "Chances of your house being damaged in the next 10 years" in the CE matrix (see Figure 1), which the variable is labelled risk; (b) Damages to the property in dollars conditional on a wildfire, is called "Damage to Property" in the CE matrix. Cost of the Program is the one-time cost for a 10-year program.

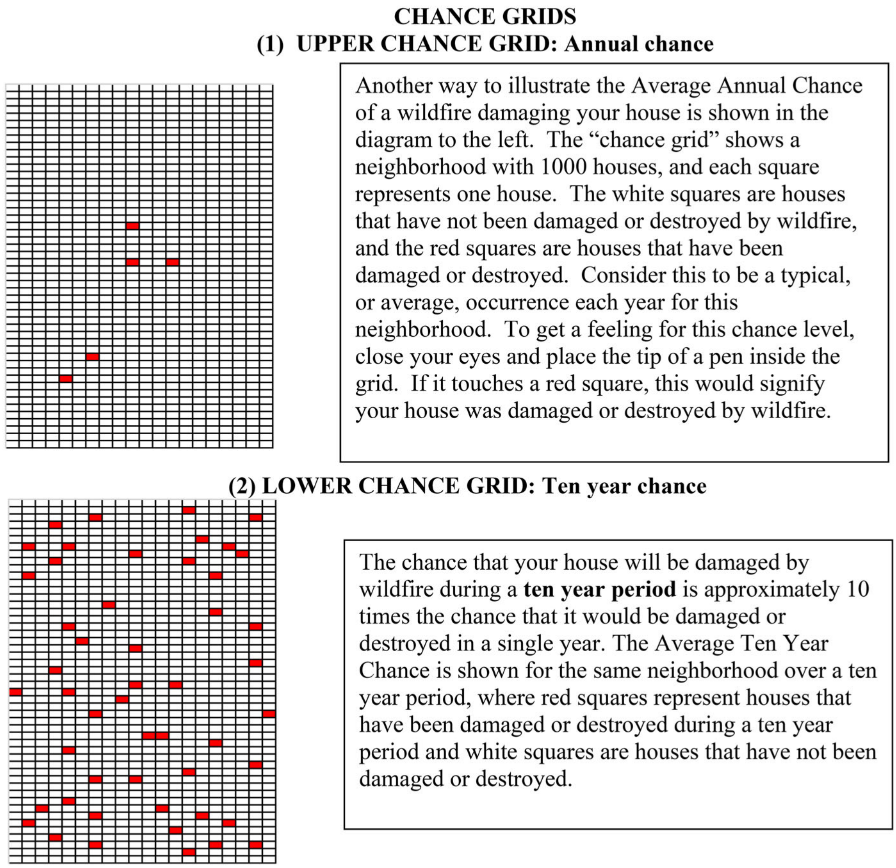

Figure 2. Risk grids to convey relevant degree of wildfire risk to homeowner survey participants (Holmes *et al*. 2013).

The survey uses four attributes to construct the choice sets (see Table 1 for number of levels for each attribute): (1) *risk* (%) is the probability of the homeowner's house being damaged by wildfires in the next 10 years (attribute varied from 1% to 5%);[3] (2) *loss* is the monetary damage to the homeowner's property from a wildfire (dollar amounts varied from $10,000 to $100,000); (3) the expected 10 year loss, which is *risk* times *loss* in order to give the respondent a better idea of the combined effect of *risk* and *loss*. Of course, this variable cannot be included in the regression for obvious reasons; and (4) *cost* is the one-time per decade lump sum *cost* to the homeowner which, in the survey, indicated it would go into a County Trust Fund to be used only for a Ten-year Vegetation Management Program (the program *cost* varied from $50 to $1,500 for the private program and from $25 to $1,500 for the public program).[4] These attributes were used to create the three alternatives (the status quo or "do nothing additional", private and public programs). The Ngene software was used to develop an efficient fractional factorial design (ChoiceMetrics 2014). The selected D-optimal design has 15 blocks, each having 3 choice sets per respondent, for a total of 45 choice sets across the entire sample. The status quo or "do nothing additional" alternative establishes a baseline of 5% wildfire *risk*, $100,000 property damage (*loss*), and $0 program *cost*. Each respondent is given three choice sets to answer in the

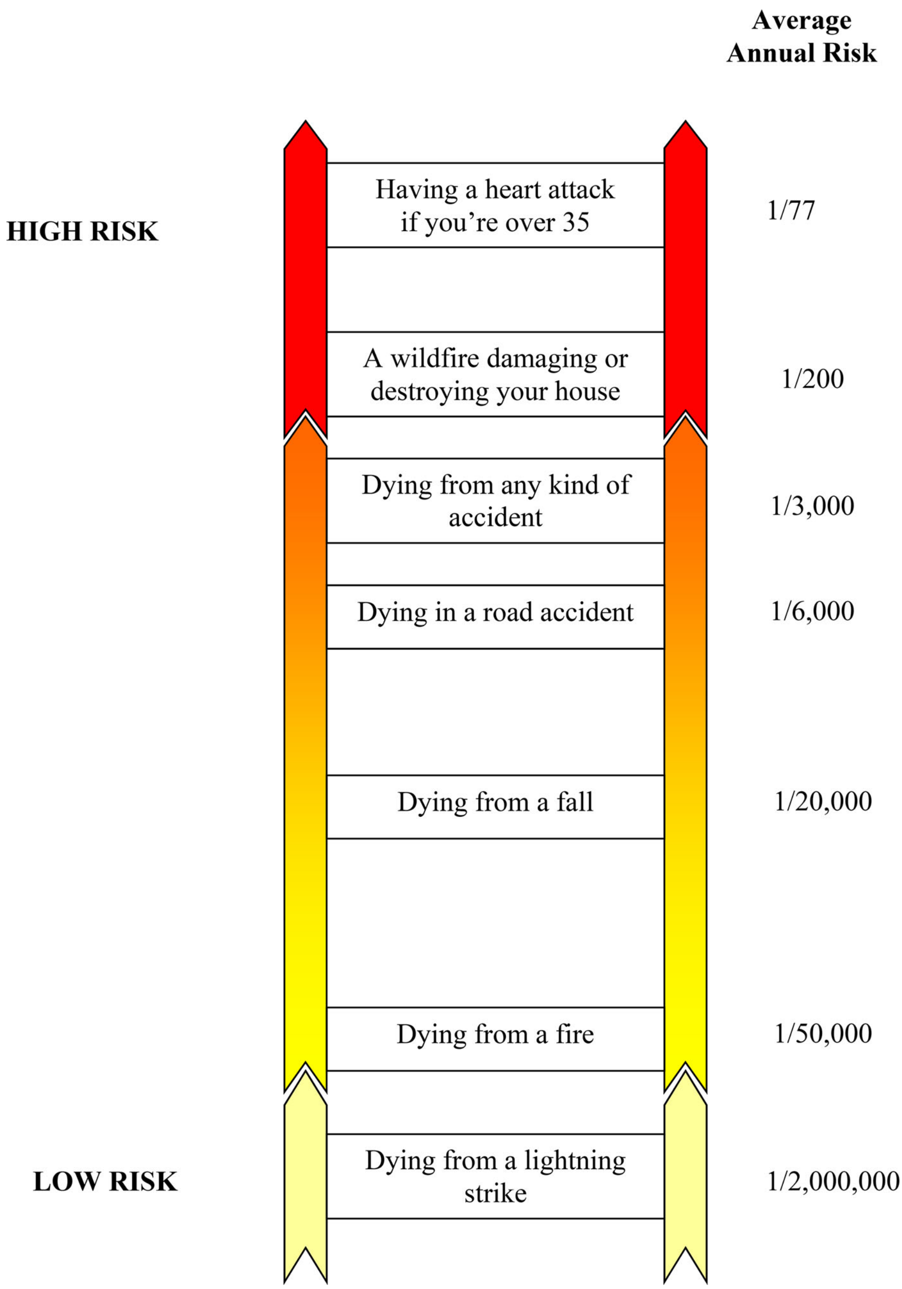

Figure 3. Risk ladder used to illustrate to survey participants the risk of wildfires relative to other, ordinary events (Holmes *et al*. 2013).

survey. Figure 1 presents an example of a choice set presented to respondents. As can be seen in Figure 1, our choice experiment is a "labeled design", since each of the alternatives have a label that provides the respondent with information distinguishing each alternative from the other. As described in the next paragraph, the Public and

Table 1. Attribute levels.

Attribute	Levels
Chance of your house being damaged in next 10 years (*risk*)	1, 2, 3, 4 and 5%
Damage to property (*loss*)	\$10 000, \$20 000, \$30 000, \$40 000, \$50 000, \$60 000, \$70 000, \$80 000, \$90 000 and \$100 000
One-time cost to you for the 10-year public program	\$25, \$50, \$100, \$200, \$400, \$600, \$800, \$1000, \$1300 and \$1500
One-time cost to you for the 10-year private program	\$50, \$100, \$200, \$400, \$600, \$800, \$1000, \$1300 and \$1500

Private Programs were described in detail in the survey to the respondent before the respondent was presented with the choice set.

As part of the survey, homeowners were asked a series of seven questions about the landscape where they live. These included four questions about shrubs and trees within 30 feet of their home. Thirty feet is a spatial area often used to determine if a home has "defensible space" to protect a home from wildfire and was illustrated on the cover of the survey. Reducing what is described in the survey as "High Fire Risk Landscaping" and "Medium Fire Risk Landscaping" with "Low Fire Risk Landscaping" is the described as "What You Can Do to Reduce Wildfire Risk". This is labelled in the survey as Private Fire Prevention option. Of course, removing trees within 30 feet of the house can change amenities of shade and privacy screening to a house. Thus, households must trade-off this change in amenities and the cost of these actions with the value of reducing fire risk and damage to their home.

The survey also asked about three questions: (1) landscaping in your neighborhood; (2) vegetation on undeveloped land; (3) vegetation on any natural areas within a half mile of their home. Fuel management such as thinning forests, mechanical removal of shrubs or a reduction in the height of shrubs, and herbicide use along with prescribed burning. These fuel reduction activities became the basis of the "Public Wildfire Prevention Methods" in the survey.

Finally, homeowners were asked to think about the descriptions of fire risk and the landscaping around their home and neighborhood and rate their fire risk as low, medium or high. We define these self-assessed fire risks as the perceived risk in our analysis and compare them to what wildfire professionals rated the area in which the homeowner lived ("objective risk").

5. Data

A stratified sample of Arizona households was collected from 2020 to 2021, with the primary focus on obtaining responses from households living in areas considered to be at meaningful risk of wildfires. Selection of survey strata used wildfire risk maps provided by the Arizona Department of Forestry and Fire Management (see Figure 4). In particular, we focused only on those homeowners facing Moderate, High/Very High, and Extreme fire risk ratings. Thus, there is a good match between homeowners in our sample and homeowners who would be eligible for the State of Arizona and USDA fuel reduction cost share grants. These are also households that very likely have come

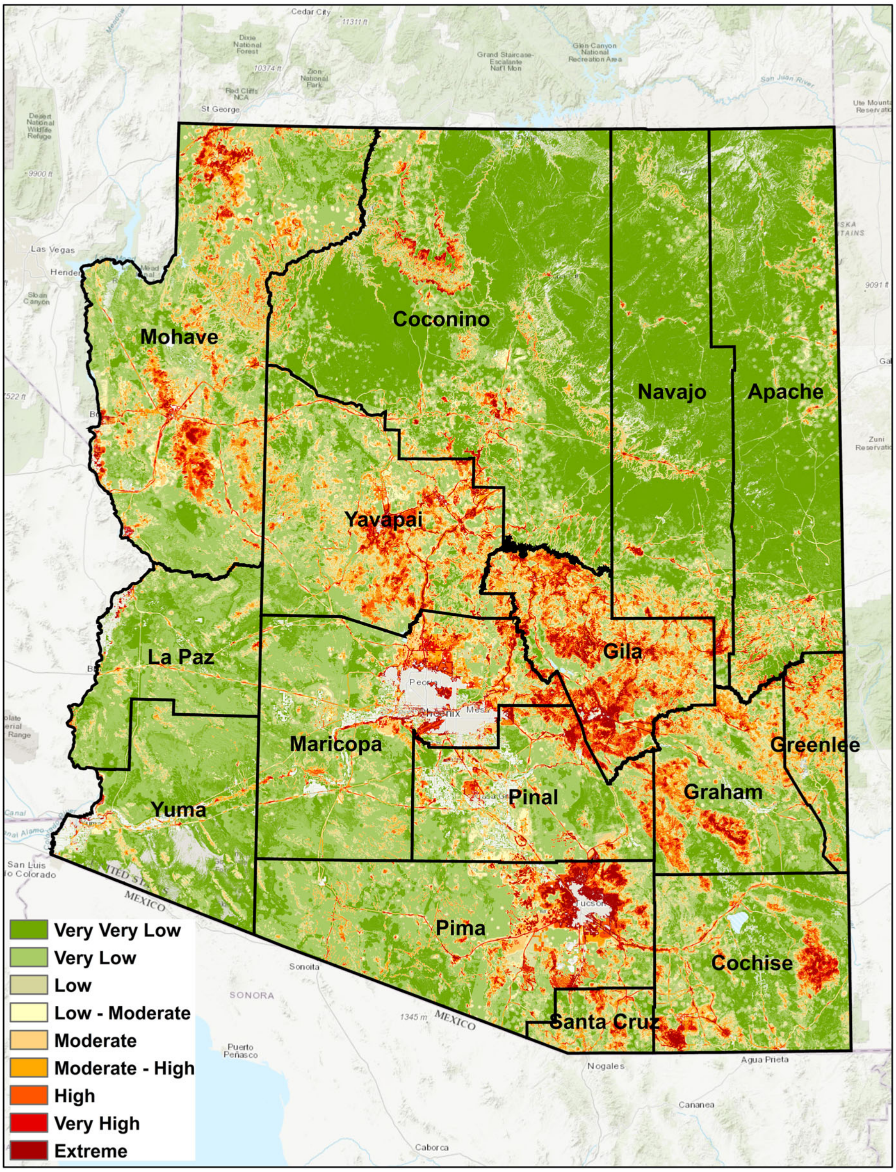

Figure 4. Wildfire risk map (source: Arizona Department of Forestry and Fire Management 2020).

across the types of cost share programs discussed in our survey, whether through demonstration projects or "open houses" in their community that are put on by county, state or federal agencies. All of these factors aided in making the survey salient to households. Our stratified sampling involved randomly sampling those living in the Extreme Fire category at a rate of three times those living in the Moderate Wildfire category. We sampled those living in the High/Very High Fire category at a rate of twice the probability of selecting residents in the residents in Moderate Wildfire category.

This procedure resulted in a sampling distribution of 44% in extreme, 28% in high/very high, and 27% in moderate. Survey data were obtained using an address-based sample with reverse look-up of phone numbers. This allowed accurate geographic targeting of households. To determine whether the households were homeowners, a screener questionnaire was administered by phone. Those households indicating they are homeowners were introduced to the purpose and importance of the survey. Their address was verified, and their email address requested so that a mixed mode survey could be implemented, as recommended by Dillman, Smyth, and Christian (2014). If the household provided an email address, then they were sent a link to the survey. Those who did not provide an email were mailed a physical letter with a link to the survey included in the letter. Four more contacts were made with non-responding homeowners to increase the response rate so that it would better represent the population of homeowners living in WUI areas of Arizona. Following the suggestion by Dillman, Smyth, and Christian (2014), a mixed mode approach was also used for the follow-up contacts.

We obtained 219 complete surveys out of 600. Among the compete surveys, we have 48 respondents who *always* choose the status quo option of no fire prevention programs.

Respondents were able to give an open-ended response to why they selected the options they did, regardless of how they voted. Eleven said their home faced no fire risk since their landscaping and those of their neighbors was primarily rock ground cover or they had no plants by their house. However, among the 48 respondents, 15 perceived they live in areas with medium or high fire risk. This response pattern may indicate a form of protest against the fuel reduction programs, since there were respondents who said, for example, “the county mismanages money”. Consequently, we refined our main sample by excluding these 15 individuals who both always chose the status quo option and perceived a significant fire risk. We conduct all analyses discussed below using the main sample.

To examine whether homeowners’ WTP for wildfire fuel reduction programs is sensitive to their perceived and objectively assessed fire risks, we gathered information on both perceived and objective risks. First, we determined the objective fire risk for respondents, assessed by professionals, by overlaying their home locations on the fire risk map provided by the Arizona Department of Forestry and Fire Management (DFFM) (see Figure 4). The DFFM developed a Wildfire Risk Assessment (AZ WRAP) based on the West Wide Risk Model (Sanborn 2013), which evaluates multiple factors influencing wildfire risk. This multi-level model includes 18 individual factors, such as fire history of an area, surface fuels, tree canopy closure, fuel type, topography and wildland development, that feed into five higher-level factors determining Fire Threat and Fire Effects. These five higher level factors include the probability of fire, fire behavior, fire suppression effectiveness, values impacted and suppression difficulty, which together create the Fire Risk Index. The Fire Risk Index categorizes risk levels from “Very Very Low” to “Extreme.” Since the survey focused on those living in the WUI, we surveyed only households in areas with a wildfire risk of moderate level or higher. In our sample, we recategorized “Moderate” as “Low,” “Moderate High” as “Moderate,” and “High,” “Very High,” and “Extreme” as “High.” Second, as we discussed in the survey design section above, we asked respondents to assess the risk of their home being damaged by wildfire as “low,” “medium,” or “high,” using this information to measure respondents’ perceived fire risk.

6. Econometric model

Choice experiments allow researchers to estimate the economic values of various attributes and attribute bundles (Holmes, Adamowicz, and Carlsson 2017; Train 2009). The choice experiment method is generally based on the random utility maximization theory, which assumes that individuals select a good or service that provides the greatest utility available to them (Champ, Boyle, and Brown 2017). The random utility model assumes the utility is the sum of systematic (V_{nj}) and stochastic (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 independent variables observed by the researcher for respondent n and alternative j, β_{nk} is a vector of preference parameters, and ε_{nj} is an error term that is unobservable to the researcher.

The basic multinomial logit (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. For this 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.[5]

The Mixed Logit Model (MLM) is a generalization of the MNL model, and allows for random variation in preferences, unrestricted substitution patterns, and correlations among unobserved factors (Train 2009). The independence of irrelevant alternatives assumption, which is imposed to estimate the MNL, may be relaxed by introducing additional stochastic components to the utility function through β_n. These components allow the preference parameters for the x_{jnk} explanatory variables to directly incorporate heterogeneity:

$$\beta_{nk} = \beta_k + \Gamma \mathrm{v}_{nk} \tag{3}$$

where β_k is the mean value for the kth preference parameter, v_{nk} is a random variable with zero mean and variance equal to one, and Γ is the main diagonal of the lower triangular matrix that provides an estimate of the standard deviation of the preference parameters across the sample. This is true only when the marginal utilities are assumed to be normally distributed across respondents and correlation of preferences across attributes is permitted.

The marginal values of each attribute are calculated using the ratio of the attribute coefficients and the negative of the cost coefficient, resulting in Equation (4):

$$MWTP_k = \frac{\beta_k}{-\beta_{cost}} \tag{4}$$

Probabilities in the MLM are weighted averages of the standard logit formula evaluated at different values of β. The weights are determined by the density function $f(\beta|\theta)$ where θ is a parameter vector describing the distribution of $f(\bullet)$. Let π_{nj} be the probability that an individual n chooses alternative j from set J, such that

$$\pi_{nj} = \int L_{nj}(BX_j)f(B|\theta)d\beta \tag{5}$$

Where

$$L_{nj}\left(\beta X_j\right) = \frac{\exp(\mu\beta X_j)}{\sum_{j=1}^{J}\exp(\mu\beta X_j)} \tag{6}$$

The function f($\beta|\theta$) can be simulated using random draws from various functional forms (Train 2009). We use Halton draws from the normal distribution to estimate Γ for the random parameters in the MLM model. The MLM captures heterogeneity *via* a continuous probability distribution for preference parameters.

6.1. *Multivariate test of perceived versus objective risk*

We conduct a multivariate test as part of our valuation model that allows us to test whether homeowners' valuation of the public fuel reduction program in their neighborhood and a private fuel reduction program around their house is influenced by their own perceived risk; and whether homeowners responses are also consistent with wildfire managers' calculation of the wildfire risk where the respondent lives. Two separate MLM regressions: one using homeowners' perceived risk, and a second one using managers' objective risk will allow us to test: (a) whether each of the two risk variables (perceived and objective) in the two equations are statistically different from zero; (b) whether the coefficients are statistically different from one another; and (c) compare the WTP for the public and private fuel reduction programs derived from the separate regressions, one of which includes homeowners' perceived risk and one including managers' objective risk.

7. Empirical results

7.1. *Sample descriptive statistics*

Table 2 compares the mean of respondents' demographic characteristics to Arizona's homeowner average demographic characteristics based on data from the 2020 US Census Bureau (2021), with standard deviations indicated within parenthesis. It shows that respondents are more likely to identify as white male, more educated, and with lower annual household income compared to the state mean. However, all of the state averages fall within one standard deviation of the sample means, showing that our sample can be considered as reasonably representative of homeowners in Arizona. Tables A1 and A2 in the Appendix also provide additional summary statistics on income and education distributions among respondents.[6]

7.2. *Comparison of perceived and objective risks*

Our results in Tables 3 and 4 show a pronounced disconnect between what homeowners perceive their risk of wildfire to their homes to be and what professional wildfire managers consider it to be, especially between the low and high levels of risk. Table 3 compares the percentage of households who perceive their wildfire risk as low, moderate, or high with the percentage of households who professionals classify as low, moderate, or high risk. Table 4 provides a more detailed cross-tabulation, breaking down how each perceived risk level (low, medium, or high) aligns with each objective risk level.

Table 2. Descriptive statistics of homeowners in Arizona ($n = 204$).

Variable	Description	Sample mean (SD)	State mean
Male	Respondent's gender; if male = 1; else = 0	0.59 (0.49)	0.49
Age	Respondent's age (years)	61.31 (14.38)	61
College	Bachelor's degree or higher; if Yes = 1; else = 0	0.62 (0.48)	0.42
Income	Household annual income ($)	$70,999 (37,365)	$87,383
Percent white	Race (selected White)	0.94 (0.23)	0.72

Table 3. Perceived versus objective risks by risk level.

	Perceived risk	Professional risk assessment
Low	67%	27%
Moderate	26%	28%
High	6%	45%

Table 4. Perceived and objective risks by risk level.

	Objective risk		
Perceived risk	Low	Medium	High
Low	71%	62%	67%
Medium	21%	33%	25%
High	7%	3%	7%
Total	100%	100%	100%

Table 3 shows that, at the low end, 67% of homeowners perceived they had a low level of risk, while based on where they live, professional fire managers' models and maps would indicate only 27% lived in an area of low risk. While there is consistency in the perceived wildfire risk of homeowners and wildfire professionals in the Moderate risk level, the disparity in the high level is striking. In particular, wildland fire maps showed that 45% of residents in the sample live in a high wildfire risk area (Table 3), among them, only 7% of them believe they live in a high risk areas, while 67% of them perceive a low fire risk (Table 4).

7.3. Basic choice experiment results: average mean marginal willingness to pay (MWTP) for public and private fire prevention programs

Table 5 Column (1) presents the results of the MLM estimated in preference-space for only those variables included in the choice matrix the respondents answered. The variables are:

Table 5. Baseline mixed logit model in preference-space and estimated MWTP. (Standard errors in parentheses.)

Attribute variable	(1) Basic preference-space model	(2) MWTP (95% CI's)
Mean		
Public program	2.193***	627.34
	(0.785)	[225.52,1029.16]
Private program	1.228	351.2
	(0.749)	[−31.39,733.79]
Risk (%)	−36.624*	−10478.22
	(20.084)	[−21474.96,518.51]
Damage ($1000)	−0.00002**	−0.005
	(0.000)	[−0.0096,−0.0003]
Costs ($)	−0.003***	
	(0.001)	
Standard deviations		
Public program	4.686***	
	(1.247)	
Private program	−3.761***	
	(0.999)	
Risk (%)	188.992***	
	(47.794)	
Loss ($1000)	−0.00004**	
	(0.00002)	
N	192	
LR chi2	24.099	
Prob > chi2	0.000	
Log likelihood	−454.475	

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.001$.

Risk: *risk (%)* of the respondents' house being damaged by wildfires in the next 10 years.

Damage: *damage ($)* to respondents' property from a wildfire.

Cost of the Program: *cost* is the one-time cost.

We assume the coefficient for the cost attribute is fixed, while all other program-related attributes are specified as normally distributed. We model the three alternatives in the choice matrix as two alternative specific constants (ASCs): one for Private Fire Prevention and one for the Public Fire Prevention Program. The trade-off between fire risk and the amenities of living in or near forest is implicit in our choice experiment and are represented by Private and Public Fire Prevention Programs. Specifically, the Private Fire Prevention Program reduces vegetation around the home as in the Firewise Program (e.g., within 30 feet of the home). The Public Fire Prevention Program reduces vegetation throughout their neighborhood. Whether the fuel reduction projects take place very close to the house itself as in the Firewise Program or throughout the community/neighborhood may matter to homeowners independent of the specific decrease in wildfire risk and damage to their homes. That is, many people move to the WUI to be in the forested environment and associated wildlife habitat. Others for the privacy or shade that the forest provides them around their home.

Holding risk and damage constant, if a homeowner prefers the fuel reduction spread throughout the community rather than around their home, they will select the Public Fire Prevention Program over the Private Fire Prevention Program and the Do Nothing Additional. If on net, most homeowners do this then the sign-on to the Public ASC would be positive and significant.

Table 5, Column (1) presents the results of the CE using an MLM in preference space. It shows heterogeneity in people's preferences for Public and Private Fire Prevention Programs as evidenced by Standard Deviations (lower half of Table 5) generally being statistically significant. In this model, we focus on just the attributes of the choice set (see Figure 1). As evidenced by the negative coefficient signs on *risk, loss and cost,* respondents derive negative utilities from higher levels of these attributes. The negative coefficient on the one-time *cost* indicates that respondents' behavior was consistent with economic principles in that the higher the cost of the alternative, all other attributes held constant, the less likely they were to select the alternative. The results of the MLM also provide evidence on the preferences toward Public Fuel Programs. The Public Program ASC coefficient is significant and positive while the Private Program ACS is positive but significant, which suggests that homeowners prefer to have a Public Program for fire prevention rather than do nothing at all, but are indifferent between a Private Program and the do nothing at all option.

Table 5 Column (2) shows respondents' MWTP along with their 95% confidence intervals for different attributes of fire prevention programs. Respondents have an average MWTP of around $627 for a one-time, 10-year cost for a Public Fire Prevention Program (see Table 5). However, the MWTP for a Private Program is positive but statistically insignificant at the 5% level. The results suggest that residents in Arizona value fire prevention programs, with a preference for public over private programs. A possible explanation is that residents believe the risk of fire to their homes would be lower if entire communities were better prepared for wildfires through activities such as removing vegetation throughout their neighborhoods. Moreover, due to the high temperatures in Arizona, residents may value having trees around their homes to provide shade.

7.4. Multivariate testing of perceived versus objective risk as a determinant of WTP

To test whether homeowners' likelihood of choosing among the three alternatives is consistent between the homeowners' perceived risk and managers' objective risk we estimate two separate MLM (see Table 6, Columns 1 and 2).[7] First, as detailed in the section on the description of the survey, the information on homeowners' *perceived* fire risk is derived directly from their answers to a question asking them to rate the risk of their home being damaged by a wildfire as "low," "moderate," or "high". These responses are used to create a dummy variable, zero if perceived risk is low and one if it is moderate or high. Second, the objective fire risk respondents face was determined by overlaying their home locations on the fire risk map developed by wildfire specialists at AZ DFFM (i.e., "objective risk"). The objective risk dummy variable is coded using the same scale as the perceived risk: zero if objective risk is low, and one if it is moderate or high. We estimate two separate MLM: the first one includes interaction terms of respondents' *perceived* fire risk dummy variable interacted with all program attributes (except cost) in the model; a second one which includes interaction terms based on *objective* fire risk dummy variable interacted with all program

Table 6. Heterogeneity in preferences and MWTP across different risk groups. (Standard errors in parentheses.)

Attribute variable	(1) Perceived risk	(2) Objective risk	(3) Perceived risk-MWTP (95% CI's)	(4) Objective risk-MWTP (95% CI's)
Mean				
Public program	1.512*	3.056*	381.64	700.23
	(0.882)	(1.589)	[−13.38,776.66]	[125.12,1275.34]
Private program	0.658	1.811	166.02	414.92
	(0.872)	(1.547)	[−239.16,571.2]	[−223.76,1053.61]
Risk (%)	2.701	−88.674**	681.87	−20321.25
	(23.864)	(42.304)	[−11067.7,12431.43]	[−38991.01,−1651.5]
Loss ($1000)	−0.00002*	−0.00003	−0.0055	−0.006
	(0.00001)	(0.00002)	[−0.0109,−0.0002]	[−0.014,0.001]
Public* High risk	3.131*	−0.368	790.48	−84.36
	(1.640)	(1.550)	[16.36,1564.6]	[−778.3,609.58]
Private* High risk	3.082*	−0.549	778.05	−125.9
	(1.618)	(1.661)	[2.57,1553.53]	[−867.54,615.74]
Risk* High risk	−135.409**	72.766	−34183.24	16675.6
	(62.896)	(50.605)	[−60172.72,−8193.76]	[−5125.5,38476.7]
Loss* High risk	−0.00001	0.0000004	−0.0029	0.0009
	(0.00002)	(0.00002)	[−0.0133,0.0075]	[−0.008,0.0099]
Cost ($)	−0.004***	−0.004***		
	(0.001)	(0.001)		
Standard deviation				
Public program	4.876***	4.992***		
	(1.412)	(1.370)		
Private program	3.545***	4.565***		
	(0.948)	(1.386)		
Risk (%)	175.126***	225.050***		
	(43.132)	(64.253)		
Loss ($1000)	0.00006***	0.00006***		
	(0.00002)	(0.00002)		
N	185	185		
LR chi2	232.290	259.152		
Prob > chi2	0.000	0.000		
Log lik.	−421.225	−431.035		

*$p < 0.1$. ** $p < 0.05$. *** $p < 0.001$.

attributes (except cost) in the model. We are particularly interested in whether respondents with different perceived and objective fire risks would have different WTPs for the private and public fuel reduction programs.

It is plausible that homeowners who perceive they live in a high fire risk area would be more likely to choose a fuel reduction program over the do nothing additional alternative. Consequently, the coefficient associated with the interactions between program ASCs and high perceived risk should be positive and significant. The results in Table 6, Column (1) show that while people who perceived that they live in low risk areas do not derive utility from the Private Program and only derive modest utility from the Public Program, with coefficients only weakly significant at 10%. In contrast, individuals who perceive their risks as medium or high derive greater utility from both programs. By comparison, results in Table 6, Column (2) based on Objective Risk indicate that neither interaction terms, whether for the Public Program*High Risk or Private Program*High Risk are significantly different than zero.

Although Table 6 Column (1) indicates the coefficients on the ASC constants for those homeowners who perceive high risks of wildfires are statistically different than zero, it is important to determine whether such differences in parameters translate into statistically significant and meaningful differences in estimated MWTP from the baseline ASC for the Public and Private Programs. In Table 6 Column (3), the coefficients associated with variables "Public Program" and "Private Program" represent MWTPs for these two programs, along with their 95% confidence intervals for homeowners who perceive low risk. In addition, the coefficients associated with the two interaction terms "Public Program*High risk" and "Private Program*High risk" indicate the additional amount homeowners are willing to pay for these programs, if they perceive that they live in moderate or high wildfire risk areas, compared to those with low perceived risk. The results reveal that homeowners with low perceived risk have a MWTP of $382 for a Public Program and $166 for a Private Program, both MWTPs are not statistically different than zero. This result is intuitive, as people who perceive low risk may not be willing to pay for any fire prevention program. However, respondents with higher perceived wildfire risks are willing to pay more for both types of programs. Specifically, compared to those with low perceived risk, individuals who perceive moderate or high wildfire risk are willing to pay an additional $790 for the Public Program and $778 for the Private Program, both of which are statistically different than zero.

While individuals with a high perceived wildfire risk are willing to pay more for both programs, their perceived risk does not align with the objective fire risk measured by experts from the AZ DFFM. As shown in Table 6, Column 4, respondents living in areas with low objective risk would pay $700 for a Public Fire Prevention Program while they do not value a Private Program. However, since the coefficients in Table 6, Column (2) on the interactions for the Public and Private Programs for homeowners living in moderate and high objective risk areas are not statistically significant, it shows that their MWTP is not statistically different from those who live in low wildfire risk areas (Table 6, Column (4)).

Overall, we find that homeowners' *two possible reasons for this discrepancy in WTP* with perceived high wildfire risks are willing to pay more for both Private and Public Fire Prevention Programs compared to homeowners living in what they perceive as low risk. However, this pattern is not evident for the same homeowners living in what fire professionals consider low, moderate and high risk. Specifically, homeowners living in areas deemed higher risk by professional foresters are not willing to pay more for either the Private or Public Program. This discrepancy may indicate significant differences between people's perceived risks and the objective risks assessed by fire experts.

7.5. Socio-economic factors that may be associated with preferences for fuel reduction

To further explore how other factors may explain participation and engagement, we estimated a latent class model, which assumes that unobserved preference heterogeneity among respondents follows a discrete distribution (Greene and Hensher 2003; Train 2009). This approach has been widely used to identify households' underlying preference heterogeneity as well as the sources of that heterogeneity (e.g., Lusk *et al*. 2018).

Using the latent class model, we first classify respondents into distinct classes based on their socioeconomic characteristics and wildfire risk profiles. We then estimate the probability that a given respondent belongs to each class and identify each class's preferences over the program attributes. Thus, the model consists of two components: one regression that predicts class membership based on respondent characteristics, and another that estimates class-specific preferences for fuel treatment attributes. Given our interest in understanding what differentiates respondents who support fuel reduction programs from those who do not, we use the latent class model to classify respondents into two groups based on individual characteristics—including objective risk, perceived risk, education (having at least a bachelor's degree), income (annual household income above $90,000), race, and gender.

Table 7 presents the estimated preferences for different features of fuel reduction programs across the two classes. In Class 1, the negative and statistically insignificant coefficients for both Public and Private Programs suggest that respondents in this group do not derive utility from either option. In contrast, respondents in Class 2 value both Public and Private Programs and experience disutility from higher wildfire risk and greater potential losses due to fire damage. Based on these patterns, we label Class 1 as "skeptics" and Class 2 as "supporters."

Column (2) of Table 7 shows how individual characteristics influence class membership. Class 2 (supporters) serves as the reference group, so the sign and statistical significance of the coefficients reflect the likelihood that a respondent belongs to Class 1 (skeptics) relative to Class 2. The results indicate that skeptics are more likely than supporters to face higher objective risk but perceive lower risk. They are also more likely to be white and have lower education levels. However, there are no statistically significant differences between the two groups in terms of income or gender.

These findings confirm our earlier result that individuals with higher perceived wildfire risk are more likely to support fuel reduction programs and, similar to past literature, that education may be an important factor in making decisions (Sánchez *et al*. 2022). The latent class model also provides additional evidence that supporters tend to be non-white and more highly educated.

8. Discussion and conclusions

Wildfires are becoming more frequent, larger, and more devastating and cause billions of dollars in property damage. In the past decade, state and federal agencies have invested nearly a billion dollars in forest fuel reduction treatments, such as prescribed burning, forest thinning, and fuel breaks. To further mitigate wildfire risks, agencies such as the USFS, state forestry departments, and local counties offer cost-sharing programs that support homeowners and communities in implementing wildfire risk reduction measures, typically requiring homeowners to contribute to project costs. However, gaps may exist between households' perceived risk and the objective risk assessed by professionals, which can affect residents' preferences and WTP for fuel reduction programs. To enhance participation, and effectively mitigate fire risks, it is essential for

Table 7. Latent class model (standard errors in parentheses).

	(1) Marginal utility for attributes		(2) Class membership determinants	
	Class1 (Skeptics)	Class2 (Supporters)		
Public program	−1.174	2.263***	Objective risk	0.489*
	(1.032)	(0.378)		(0.258)
Private program	−2.050	1.981***	Perceived risk	−2.164*
	(1.257)	(0.386)		(1.128)
Risk (%)	100.116**	−21.963***	Male	−0.119
	(39.261)	(6.054)		(0.434)
Loss ($1000)	−0.000001	−0.000008***	Hispanic	−0.213
	(0.00001)	(0.0000003)		(0.788)
Cost ($)	−0.001	−0.001***	White	1.972*
	(0.001)	(0.000)		(1.108)
			High education	−0.801*
				(0.435)
			High income	−0.275
				(0.426)
			Constant	−0.834
				(1.626)
N	185			

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

managers to understand residents' program preferences and how homeowners' risk perceptions influence participation.

We conducted a CE survey in Arizona to assess homeowners' preferences for Public and Private Fire Prevention Programs. Homeowners in Arizona are willing to pay, on average, a one-time fee of approximately $627 for a public wildfire mitigation program. However, they are not willing to mitigate wildfire risk through private programs. This finding suggests that homeowners prefer the fuel reduction to be spread throughout the community rather than only around their home. One possible explanation is that shade from trees around homes is particularly important for cooling, given Arizona's hot climate. Therefore, future wildfire mitigation programs should consider local climate conditions and residents' preferences. Policymakers may consider prioritizing funding and implementing fuel reduction programs that align with community demands and provide broad, equitable benefits.

We also compare the effect of homeowners' perceived risk with objective risk assessments provided by wildfire professionals on their WTP for fuel reduction programs. The results show that among homeowners who perceived they had a moderate to high risk of wildfires there were statistically significant homeowner preferences for, and one-time WTP for, public ($790) and private ($778) fuel reduction programs. Those homeowners perceiving that they had low wildfire risk did not prefer, and would not pay for, the fuel reduction programs. Moreover, while homeowners living in low objective risk areas had a one-time WTP of $700 for the Public Program, homeowners who lived in areas with moderate to high objective risk were no more likely than those who lived in low-risk areas to want to pay for the fuel reduction programs.

These results are qualitatively similar to the past literature on everyday risks, natural hazards, or even wildfire risks (Meldrum *et al*. 2015). The difference in risk perception translates into 45% of homeowners actually living in what professionals consider high risk wildfire areas when only 6% think they do. However, our results go beyond past literature in an important policy relevant way. Based on the findings in Tables 3 and 4, among the 45% of homeowners who actually live in high-risk areas, only 7% believe they are in high-risk areas, while 67% perceive that they face low wildfire risk. Households are not willing to pay for fire prevention programs if they perceive the fire risk as low, even when they objectively reside in high-risk areas. This raises concerns about the feasibility of collecting sufficient funding for fire mitigation cost-sharing programs. While households who perceive that they live in moderate- to high-risk wildfire areas are willing to pay approximately $800 for each of the two fuel reduction projects (both private and public programs), this amount is likely insufficient to reduce the high wildfire risk to a level where firefighters can successfully contain a wildfire or save homes.

There are two possible reasons for this discrepancy in WTP. First, professional risk assessments include determinants of fire risk that may be overlooked or not understood by the public. For example, the steepness of any hillsides near to the house has a strong effect on the rate of spread of a wildfire (Payne, Andrews, and Laven 1996). These more technical factors may not be considered, or its effect on wildfire risk and damage may be underestimated by households when assessing their own wildfire risks. Such discrepancies between expert risk assessments and household perceptions highlight the need for targeted education and effective messaging to align public understanding with expert evaluations. Thus, communicating objective risk widely may be helpful, *ex ante* such that potential buyers can factor in variables that increase wildfire risk but are not modifiable *ex post* by homeowners. Maps of the State of Washington by the firm First Street provide wildfire risk information at the zip code level (Moss 2023) not only for the current time period but forecast into the future to account for climate change.

Second, it is possible that the current professional risk assessments, whether by state agencies such as AZ Department of Forestry and Fire Protection or private firms, including homeowner insurance companies such as Nationwide and Pemco (Moss 2023) need a finer scale than zip code. In this case, a more accurate and finer spatial scale risk map can be an essential tool for informing homeowners about the wildfire risk they face. For instance, Colorado Springs has taken early steps to generate highly detailed fire risk maps approximating to parcel level to improve the accuracy of professional fire risk assessments (Donovan, Champ, and Butry 2007). Such efforts may provide granular and up-to-date mapping tools in bridging the gap between perceived and actual wildfire risk and in fostering more effective community wildfire mitigation efforts. Currently providing this information *ex-post to existing homeowners* is not without controversy. Advances in resolution of Landsat satellite imagery can identify vegetation around individual houses in some WUI areas with large lot areas. This private information has, in some cases, been used to set individual homeowner insurance rates, and in some cases even to cancel insurance. For instance, several major insurers have pulled out of the state or drastically reduced coverage in high-risk areas, citing unsustainable losses. This retreat has forced many homeowners onto the California FAIR Plan, which is a state-mandated insurance program designed to provide basic property insurance but with limited coverage for homeowners. Thus, there has been a pushback in California[8] and in Oregon to basing homeowner insurance rates on such data. However, California is working with insurance companies to not only inform homeowners of the risks they face but what they can do to reduce those risks and, hence, the cost of their homeowners' insurance,[9] through measures such as home hardening and participation in Firewise USA® programs. This use of insurance rates may help to bring homeowners' perceived risk more in line with objective risk in the future. Longitudinal surveys over this next decade would likely be very informative on the role of the homeowners' insurance market in aligning perceived risk with the objective of risks from companies that have billions of dollars at stake.

A practical proposed way of reducing the disparity between managers' objective risk and homeowners' perceived risk is at the time buyers are considering the purchase of a house. Our proposal is to include managers' rating of neighborhood wildfire risk and expected insurability on an updated Multiple Listing Service[10] (commonly known as MLS) sheets that realtors have access to and give to prospective buyers. This allows factors that managers consider in their ratings to be disclosed to buyers. These MLS sheets are often included in boxes outside houses for sale, and at "Open Houses" when realtors show homes they have listed. In this way, prospective homeowners' perceived risk at the time of buying could be better aligned with wildfire managers' objective risk. Further, adding to the MLS information on whether homeowners' insurance is available in that area may better align perceived and objective risk at the time of the purchase.

While more public information efforts on wildfire risk and Firewise may continue to chip away at the disparity between perceived and actual risk, two trends may help to reduce the disparities even further. First, wildfires are becoming less of a rare event, with more and more people directly experiencing fire evacuations, and millions breathing wildfire smoke. Wildfires are no longer confined to a short well-defined season but, for many western US states such as Arizona and California, are a year-round occurrence. At the same time, fires are getting larger and larger and sometimes individual fires are merging into what are known as a "fire complex". More recent and repeated experience with larger and larger wildfires may help to reduce the disparity between perceived fire risk and actual fire risk (Wachinger *et al*. 2013).

Second, the recent risk-related homeowner insurance ratings that have markedly increased insurance costs for those living in high wildfire risk areas has been a wake-up call for homeowners who believed they were in low wildfire risk areas. While the initial reaction was outrage, the legislative calls in California, Oregon, and Washington for transparency in how these wildfire risk ratings are calculated have the potential to educate homeowners on many of the same factors that wildfire professionals have been using for more than a decade. In this regard, we may see a narrowing of the gap between perceived risk and objective risk among those living in the wildland urban areas in the next decade. Longitudinal surveys over this next decade would likely be very informative on the role of the homeowners' insurance market in aligning perceived risk with the objective of risks from companies that have billions of dollars at stake.

Notes

1. Surprisingly, what would seem to an expert to be an unusual homeowner response to actual fires observed in homeowner property value studies of the effect of wildfire. Shi *et al.* (2022) used house sales data in Colorado from 2000-2016, and found that large fires can *increase* property values in WUI areas, and small fires reduce property values.
2. In the FEMA (2024) map, the tab for Wildfire Risk only is used to isolate wildfire for AZ from all other natural hazard risks.

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 they were shown but not in the econometric model, since that variable would be redundant with the two individual variables.
5. 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 dataset, the scale parameter cannot be recovered.
6. While we know the income distribution of our respondents, we do not ask for their source of income, for instance, whether their household income is generated from forest-related activities. Having income being tied to forest-based activities, may influence their incentives for supporting fuel reduction programs. Since we surveyed in the wildland urban interface, and Arizona is not known for being a major timber producing area (less than 1% of State GDP), it is unlikely homeowners have much forest related income. Nonetheless, future research could further explore this relationship.
7. Respondents with missing data on perceived fire risks are not included in the analysis.
8. https://www.insurance.ca.gov/01-consumers/200-wrr/WildfireRiskInfoRpt.cfm.
9. https://www.insurance.ca.gov/01-consumers/105-type/95-guides/03-res/upload/FAQ-Safer-from-Wildfire-Regulation.pdf.
10. The MLS form is designed and updated by the Real Estate Standards Orgnaization. However, individual states often have different legally required information, so each state's forms may vary slightly from each other.

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Appendix

Table A1. Distribution of education levels.

Education level	Percent
Less than high school	0.9%
High school graduate	5.5%
Some college or technical school/associate's degree	28.3%
College graduate	31.5%
Postgraduate	29.2%

Table A2. Distribution of annual household income levels.

Annual household income	Percent
Less than $9,999	1.4%
$10,000–$14,999	1.4%
$15,000–$29,999	3.7%
$30,000–$44,999	5.0%
$45,000–$59,999	14.6%
$60,000–$74,999	9.6%
$75,000–89,999	10.5%
$90,000–$104,999	12.8%
$105,000–$119,999	7.3%
$120,000 or more	23.3%