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The effects of personal experience on choice-based preferences for wildfire protection programs

Thomas P. Holmes[A,D], *Armando González-Cabán*[B], *John Loomis*[C] *and José Sánchez*[B]

[A]Southern Research Station, USDA Forest Service, PO Box 12254, Research Triangle Park, NC 27709, USA.
[B]Pacific Southwest Research Station, USDA Forest Service, 4955 Canyon Crest Drive, Riverside, CA 92507, USA.
[C]Department of Agricultural and Resource Economics, Colorado State University, B310 Clark Building, Fort Collins, CO 80526, USA.
[D]Corresponding author. Email: tholmes@fs.fed.us

Abstract. In this paper, we investigate homeowner preferences and willingness to pay for wildfire protection programs using a choice experiment with three attributes: risk, loss and cost. Preference heterogeneity among survey respondents was examined using three econometric models and risk preferences were evaluated by comparing willingness to pay for wildfire protection programs against expected monetary losses. The results showed that while nearly all respondents had risk seeking preferences, a small segment of respondents were risk neutral or risk averse. Only respondents who had personal experience with the effects of wildfire consistently made trade-offs among risk, loss and cost and these respondents were willing to pay more for wildfire protection programs than were respondents without prior experience of the effects of wildfire. The degree to which people with prior experience with the effects of wildfire can effectively articulate an economic rationale for investing in wildfire protection to other members of their own or other communities facing the threat of wildfires may influence the overall success of wildfire protection programs.

Additional keywords: expected utility, heuristics, natural disasters, prospect theory, risk aversion, risk seeking.

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Introduction

Wildfires pose a risk of catastrophic loss of life and property for people living in fire-prone natural landscapes. The increasing frequency and severity of wildfires in forested residential neighbourhoods in the United States has caused fire managers and policy-makers to emphasise the role of homeowner and community mitigation activities to reduce the hazards associated with wildfires (National Fire Plan 2001). However, little is known about the efficacy of these approaches or the factors that influence the degree to which homeowners and communities are willing to invest time, effort and money in hazard mitigation (Holmes *et al.* 2007). Further, community-based wildfire hazard mitigation programs represent a weakest link public good wherein each member of a community has a '…kind of veto power over the extent of collective achievement' (Hirshleifer 1983, p. 373). The landscape-scale provision of wildfire protection is compromised by homeowners within a community who fail to take hazard mitigation actions, thereby increasing the risk for other members in the community. Understanding the factors that influence decisions of whether, and how much, to invest in wildfire hazard mitigation activities will help to identify obstacles to the implementation of efficient and effective fire mitigation programs and policies.

A popular approach for evaluating willingness to pay (WTP) for environmental programs is the contingent valuation method, which asks people to respond to payment questions regarding hypothetical scenarios (Boyle 2003). In the first application of the contingent valuation method to the evaluation of wildfire protection programs, Winter and Fried (2001) (using an open-ended payment format) found that the average amount that homeowners were willing to pay to reduce fire risk to their home by 50% in a fire-prone (jack pine, *Pinus banksiana*) landscape in Michigan was modest ($57 per year). They also reported that more than one-quarter of respondents were not willing to pay anything because they viewed the risk as too small to worry about. More recently, Talberth and colleagues (2006) conducted a contingent valuation study (also using an open-ended payment format) of homeowner WTP for wildfire programs that would reduce wildfire risk to private residences, neighbourhoods and public lands in a fire prone region of New Mexico. In contrast to Winter and Fried (2001), they reported that the average WTP estimates for protecting one's private residence were substantial ($240 per year). Lower WTP values were reported for reducing neighbourhood fire risk ($94 per year) and fire risk on public lands ($64 per year).

In contrast to open-ended contingent valuation payment formats, Loomis and colleagues (2009) used a binomial choice response format in which respondents were asked whether or not they would vote in favour of fuel reduction programs in their state if it cost them a specified amount of money.[A] One of the ways in which the internal validity of WTP estimates can be evaluated is by testing whether estimated values are consistent with economic theory (Arrow *et al.* 1993). Loomis and colleagues (2009) found that estimated WTP values were sensitive to the scope of the fuel reduction programs, providing evidence that responses represented true economic values.

An alternative method for estimating willingness to pay for environmental programs is based on a choice experiment in which survey respondents are asked to choose among alternative programs that vary in program attributes and price (Holmes and Adamowicz 2003). One advantage of the choice experiment is that it allows analysts to evaluate WTP for a wide variety of program attribute levels in a single survey. In this paper, we use a choice experiment to estimate WTP for wildfire programs that would reduce both wildfire risk and potential value lost to homeowners due to wildfire damage. We evaluate the reasonableness of survey responses by comparing estimated values with the predictions of alternative theoretical models of decision-making under risk as well as with other empirical studies reported in the literature.

In the next section we provide a brief review of some salient literature describing decision-making under risk. This is followed by a description of our empirical models and survey methods. Empirical results are presented in the following section and, finally, our conclusions are presented and discussed.

Decision-making under risk

Several alternative theoretical models are available that describe decision-making under conditions of risk, and the standard economic model is based on expected utility (EU) theory (Schoemaker 1982). As used in economic analysis, a utility function is a convenient (axiomatic) way to describe individual preferences over possible consumption bundles (Varian 1984). EU theory is based on the proposition that people make choices so that expected utility is maximised, where expected utility is computed as the sum of the utility associated with each possible outcome multiplied by its probability. It is assumed that the individual's utility function is concave in wealth (increases at a decreasing rate as wealth increases) and, when faced with risky choices, decision-makers are risk averse regarding losses (Deaton and Muellbauer 1980). Within the context of wildland fire, the EU model predicts that homeowners would be willing to invest in wildfire protection programs an amount that exceeds the actuarial value of the potential loss of wealth due to wildfire damage.

Despite the popularity of the EU model, a substantial body of empirical evidence suggests that EU maximisation is more the exception than the rule, especially at the individual decision-making level (Schoemaker 1982; Harless and Camerer 1994; Starmer 2000). Responding to various critiques of EU theory, an alternative theory of choice under risk known as prospect theory has gained popularity (Kahneman and Tversky 1979). These authors argued that prospect theory generalises EU theory in several dimensions: (1) the individual's value function is defined on changes from a reference point (not on absolute amounts), (2) the value function is convex (decreases at a decreasing rate) for losses in wealth, (3) probabilities are treated as decision weights rather than as purely objective mathematical constructs and (4) simplification rules are used to facilitate decision-making in complex situations. In contrast to EU theory, the value function proposed by prospect theory predicts that when faced with the risk of a loss of wealth, people are generally risk seeking. Thus, when considering how much to invest in a wildfire protection program that reduces the expected loss from wildfire, prospect theory predicts that people will be willing to pay less than the actuarial value of a potential loss. Kahneman and Tversky (1979) argue that this type of behaviour results because people overweight a certain loss (the payment) relative to a probable loss (the gamble).

Although the annual risk of a wildfire damaging or destroying a home is generally very low in fire prone landscapes, the consequences of wildfire can be extreme to homeowners.[B] It has been recognised that individuals tend to reject insurance under low-risk high-consequence (LRHC) conditions, despite the fact that standard economic theory suggests that people would purchase insurance against the low probability of a catastrophic loss (Kunreuther and Slovic 1978). In contrast to the idea that individuals make decisions that are entirely rational in an economic sense, it has been shown that, under conditions of low risk, people tend to use *ad hoc* decision rules or heuristics that simplify decision-making (Camerer and Kunreuther 1989).[C] For example, in laboratory experiments designed to evaluate how individuals make risk–loss–cost tradeoffs, decisions are often simplified by discounting risk entirely, thinking that 'it can't happen to me' (McClelland *et al.* 1993) or by focusing on risk and discounting losses (Ganderton *et al.* 2000). Another salient heuristic that is used when evaluating LRHC events is to overestimate or exaggerate the risk, especially if similar events are easy to recall (Tversky and Kahneman 1973). It has been found, for example, that the demand for flood insurance is highly correlated with the level

[A]This response format is preferred to the open-ended format as it closely mimics actual market decisions (Boyle 2003).

[B]In temperate forests, natural disturbances (e.g. fires, insect epidemics, windstorms) affect, on average, ~1% of the forest landscape per annum, a value that ranges between ~0.5 and 2% across a variety of ecosystems (Runkle 1985). Fire protection programs lower the risk of wildfires damaging or destroying residential structures, so the annual risk would be less than 1% in most locations.

[C]It has been argued by Gigerenzer (2001) that people select from a set of fast (time-limited) and frugal (knowledge-limited) heuristics in making most decisions, and that the choice of heuristic is context dependent.

of flood losses in the previous year (Browne and Hoyt 2000), and that past personal experience of a catastrophe makes individuals more pessimistic regarding potentially catastrophic future events (Cohen *et al.* 2008).

Empirical methods

In this study, a choice experiment was designed to estimate homeowner WTP for programs that reduce the risks (probabilities of damage) and economic losses from wildfires and to evaluate the degree to which individuals make fully compensatory decisions when evaluating risk–loss–cost tradeoffs.[D] Recognising that risk perceptions and preferences may vary across individuals and that homeowners may select from a variety of decision rules when making choices regarding wildfire mitigation, three types of econometric models that focus attention on preference heterogeneity were estimated and compared. The standard multinomial logit model (MNL) allows analysis of preference heterogeneity by interacting respondent characteristics with the attributes of choice set alternatives. However, MNL cannot capture *unobserved* preference heterogeneity or handle correlations induced by panel data arising from multiple responses from the same person. Consequently, we specified two further models that address these limitations: random parameter logit (RPL) and latent class analysis (LC). In all three models we test the hypothesis that preferences regarding the risk and economic loss reduction aspects of wildfire mitigation programs reflect, to some degree, the prior experience of respondents with actual wildfires as well as their subjective perception of risk.

Econometric models

The standard MNL model is based on the idea that when faced with more than one alternative in a given choice set, respondents choose the alternative that provides them with the greatest utility. Random utility models are based on the notion that utility is the sum of systematic (V_{nj}) and random (ε_{nj}) components:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \equiv \sum_{k=1}^{K} \beta_{nk} x_{jnk} + \varepsilon_{nj} \qquad (1)$$

where x_{jnk} is a vector of K explanatory variables observed by the analyst for alternative j and respondent n, β_{nk} is a vector of preference parameters and ε_{jn} is an unobserved stochastic variable. 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:

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

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

The RPL model is a generalised form of the MNL model, and allows for random variation in preferences, unrestricted substitution patterns and correlations among unobserved factors (Train 2002). The independence of irrelevant alternatives assumption, which is imposed to estimate the MNL model, 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:

$$\beta_{nk} = \beta_k + \Gamma v_{nk} \qquad (3)$$

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.

Probabilities in the RPL model are weighted averages of the standard logit formula evaluated at different values of β, where 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:

$$\pi_{nj} = \int L_{nj}(\beta X_j) f(\beta) d\beta \qquad (4)$$

where:

$$L_{nj}(\beta X_j) = \frac{\exp(\mu\beta X_j)}{\sum_{j=1}^{J} \exp(\mu\beta X_j)} \qquad (5)$$

The function $f(\beta|\theta)$ can be simulated using random draws from various functional forms (Train 2002). For the analysis reported in this paper, we use 500 Halton draws from a standard normal density function to estimate Γ for the random parameters.[F]

The RPL model captures heterogeneity via a continuous probability distribution for preference parameters. In contrast,

[D]Decisions that reflect tradeoffs among all the attributes of alternatives are referred to as compensatory decision rules, whereas simplifying strategies that ignore some tradeoffs are referred to as non-compensatory decision rules. Non-compensatory strategies are heuristics that simplify the processing of information so that some or all tradeoffs are ignored in problems of choice (Payne and Bettman 2001).

[E]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. However, as discussed below, WTP values are a function of the ratio of β parameters, so the scale parameters cancel out.

[F]Halton draws differ from random draws from a specified distribution. The sequence of Halton values provides efficient coverage using an algorithm in which each subsequence in the process fills in the gaps of the previous subsequences. Computer time can be greatly reduced using a Halton sequence relative to random draws while increasing accuracy (Train 2002). The gain in efficiency is largely due to the fact that random draws can create clusters of values that add little information. Halton draws from a standard normal density proceed by evaluating the inverse cumulative distribution at each element of the Halton sequence, thereby dividing the density into segments of equal mass (Train 2002, pp. 228–229).

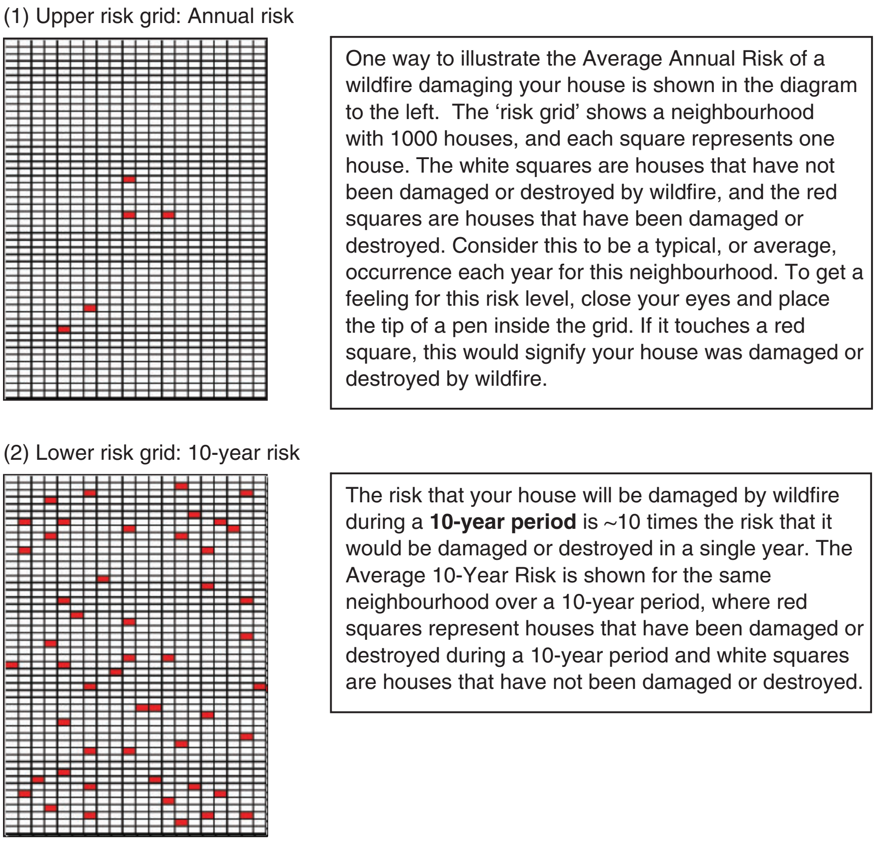

Fig. 1. Risk grids used to convey relevant degree of wildfire risk to homeowner survey participants.

the latent class (LC) model captures preference heterogeneity for a finite number of heterogeneity classes (Boxall and Adamowicz 2002; Scarpa and Thiene 2005). The preference parameters are specific to each class (c) in a population, and the choice probability for alternative j for each class is:

$$\pi_{n|c}(j) = \frac{\exp(\mu_c \beta_c X_j)}{\sum_{k \in C} \exp(\mu_k \beta_c X_k)} \tag{6}$$

where C is the set of all classes. The probability that an individual falls within a class is given by a membership function:

$$\pi_{nc} = \frac{\exp(\alpha \gamma_c Z_n)}{\sum_{c=1}^{C} \exp(\alpha \gamma_c Z_n)} \tag{7}$$

where γ_c is a scale parameter (set equal to one) and Z_n is a vector of variables describing individual characteristics. The joint probability that an individual belongs to class c and chooses alternative j is simply the product of Eqns 6 and 7:

$$\pi_n(i) = \sum_{c=1}^{C} \pi_{nc} \pi_{n|c} \tag{8}$$

This model specifies that the choice of an alternative is a function of both the attributes of the alternatives as well as respondent characteristics.

Model specifications

One of the dominant challenges associated with evaluating preferences regarding wildfire protection is that the risk of a home being damaged or destroyed by wildfire is very low. In this study, we follow the approach of Krupnick and colleagues (2002) who developed a contingent valuation format to study the effect of age and health status on WTP for mortality risk reductions.[G] We modified their format by posing a situation where the risk of a home being damaged by a wildfire was represented, on a 1000-square lattice, by a red square and the risk of being undamaged was represented by a white square. To simplify the conceptualisation of the risk of a wildfire damaging a home, we asked respondents to consider the actual risk that their home might be damaged by wildfire during the next decade (Fig. 1). Further, to convey the relative risk of a wildfire damaging a home relative to other ordinary risks (such as having a heart attack for a person over 35 years of age), a risk ladder was presented to respondents (Fig. 2).

Our survey design varied the *risk* of private property damage during a 10-year period over five levels, from 1 to 5%, where 5%

[G]A similar design was used more recently in a choice experiment by Adamowicz *et al.* (2011).

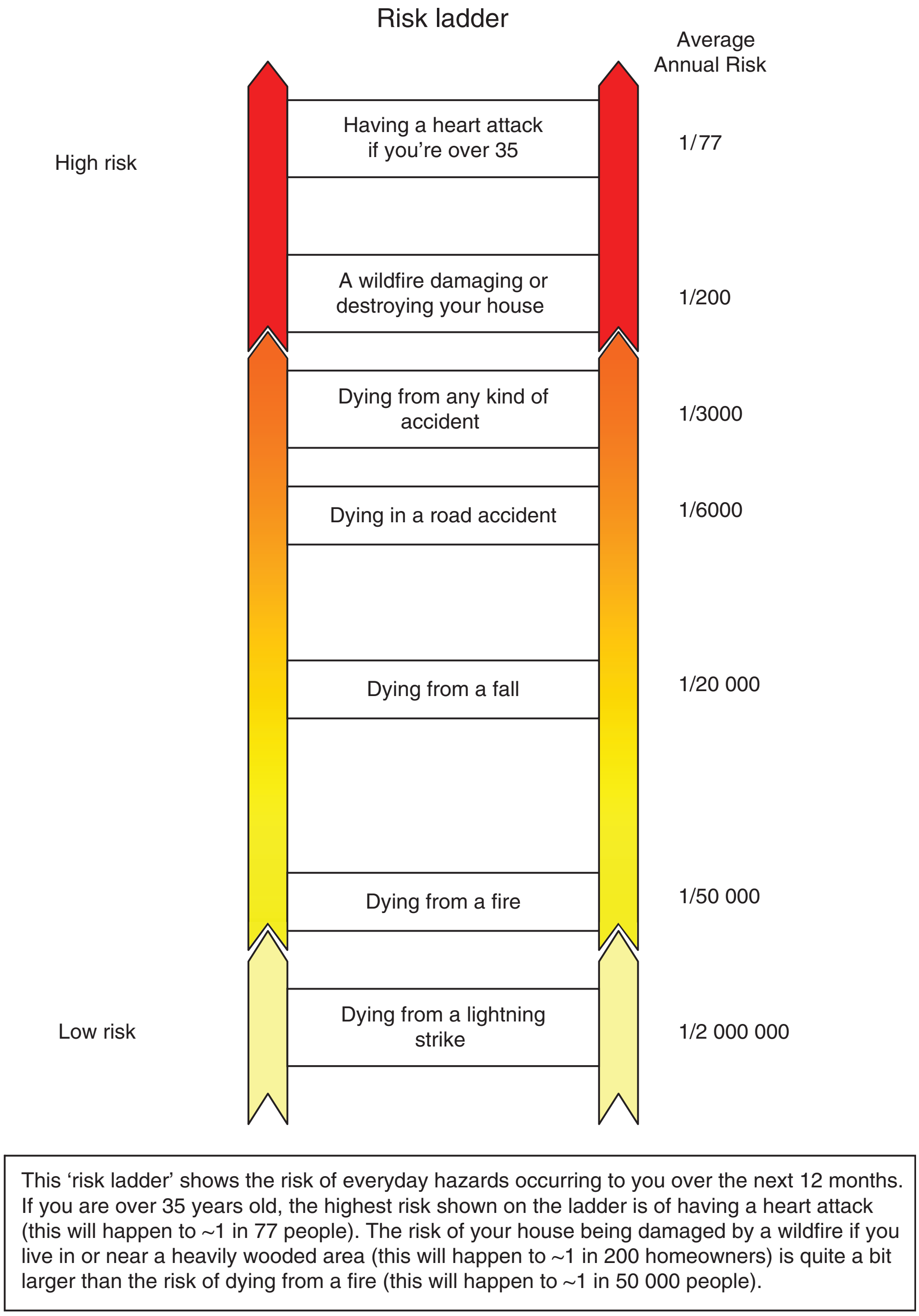

Fig. 2. Risk ladder used to illustrate to survey participants the risk of wildfires relative to other, ordinary daily events.

was the baseline *risk* associated with no new investments in wildfire protection programs.[H] Damages from wildfires were posed in terms of economic *loss* to property values with dollar amounts ranging from \$10 000 to \$100 000. The *cost* of these programs varied from \$25 to \$1000 for a public program and from \$50 to \$1000 for a private program.

Two types of wildfire mitigation programs were included in the experiment: a public program and a private program. The public program would include activities commonly used in Florida for managing vegetation and reducing fuels in forests and undeveloped areas near neighbourhoods (prescribed burning, mechanical treatment and herbicide treatment), and would be funded by a tax increase. The private program would increase the defensible space (DS) on the respondents' property by managing vegetation, such as removing trees close to the house. Alternative–specific constants (ASCs) were specified in the

[H]We use *italic* to denote variables used in the empirical analysis.

Question 20	Alternative #1	Alternative #2	Alternative #3
	Public fire prevention	Private fire prevention	Do nothing additional
Risk of your house being damaged in next 10 years	40 in 1000 (4%)	10 in 1000 (1%)	50 in 1000 (5%)
Damage to property	\$40 000	\$80 000	\$100 000
Expected 10-year loss = Risk × damage	\$1600 during 10 years	\$800 during 10 years	\$5000 during 10 years
One time cost to you for the 10-year program	\$300	\$100	\$0
I would choose: Please check one box	☐	☐	☐

Fig. 3. Example of a choice question included in the homeowner survey to evaluate tradeoffs between wildfire risk, damage and program cost.

empirical models for the public (*public_program*) and private (*private_program*) wildfire protection programs. Because the value of these programs may vary according to the respondents' subjective evaluation of the fire risk they face in their community, we created a dummy variable to identify respondents who indicated that they perceive their home is located in a high (*v.* medium or low) fire risk area. This variable was then interacted with ASCs to create two new variables (*public program × high risk*, *private program × high risk*). Finally, recognising that people who have previously conducted private wildfire protection activities on their property may have a lower WTP for public risk protection programs, we created a variable (*public program × DS*) to test for this effect.

Two variables were used to capture the influence of respondent experience with actual wildfires. First, we created a dummy variable based on responses to the question 'Has your health or the health of anyone else in your family, ever suffered from breathing smoke from a wildfire?', which was coded as unity if the response was affirmative and zero otherwise. Second, we created another dummy variable based on responses to the question 'Have you ever had to change your travel plans because of a wildfire?', again with unity representing the affirmative response. If either of these two variables was coded as unity, a new variable, *personal experience*, was coded as unity. The influence of *personal experience* on the mean of the preference parameters for *risk* and *loss* was evaluated by interacting *personal experience* with these variables in both the MNL and RPL models. This variable was entered as a covariate explaining latent class membership the LC model.

Experimental design and survey development.

A completely randomised experimental design was used to construct the choice sets (Holmes and Adamowicz 2003). Although this design is not as efficient as optimised experimental designs, it mimics a full factorial design and is easy to program using a spreadsheet.[I] Potentially unique combinations of attribute levels were thus created for each choice set and respondent. Three alternatives were given in each choice set (Fig. 3). The first two alternatives represented public and private risk mitigation programs. In addition, a status quo alternative was included at zero cost, representing a typical current situation, and a series of three choice questions were asked to each respondent.

An initial version of the survey was presented to three focus groups – in low, medium and high wildfire risk areas – to evaluate study design, clarity of wording, use of graphics, range of values used and to consider if important issues were omitted or obscured. Revised versions of the survey were then pretested on a sample of 100 respondents to evaluate whether or not respondents were answering questions in a sensible manner. The final version of the survey was distributed using a stratified random sample.

Survey sample

A stratified random sample of households living in single-family, owner-occupied residences was drawn from the population of households in Florida. Because it was thought that people living in areas that have a higher risk of damage from wildfires would be more concerned about wildfire protection programs, we developed a weighting scheme where, for each household sampled from low risk communities, two households were sampled from medium risk communities and three households were sampled from high risk communities (as defined by the Florida Forest Service). Households were recruited using random digit dialling, and basic information was recorded during an initial phone call. Then, households that were willing to participate in the survey were mailed a survey booklet. Within two weeks of receiving the booklet, a return

[I]For a good reference on alternative experimental designs, see Louviere Hensher and Swait (2000). We note that the correlation coefficients among attribute levels for the completely randomised design we used were very low: cost–loss, cost–risk and loss–risk coefficients were 0.002, 0.021 and 0.034.

Table 1. Descriptive statistics of homeowner survey responses for variables included in the econometric model specifications

Variable	Description	Mean (s.d.)
Health (dummy variable)	Health of respondent or family member suffered from breathing smoke from wildfire; if Yes = 1; else = 0	0.15 (0.35)
Travel (dummy variable)	Household travel plans changed because of a wildfire; if Yes = 1; else = 0	0.35 (0.48)
Personal experience (dummy variable)	If either (health = 1 or travel = 1) = 1; else = 0	0.43 (0.50)
Defensive space (DS) (dummy variable)	Household conducted at least one activity that reduces wildfire risk; if Yes = 1; else = 0	0.76 (0.43)
High risk (dummy variable)	Respondent indicated that home is located in a high fire risk neighbourhood; if Yes = 1; else = 0	0.10 (0.30)

phone call was made to households and responses to the survey questions were recorded by the phone interviewer. Overall, our analysis is based on 922 complete interviews.

Estimating WTP and risk profiles

The choice experiment framework permits a WTP measure to be estimated for each attribute, which is often referred to as the implicit price or part-worth of that attribute (Bennett and Adamowicz 2001; Holmes and Adamowicz 2003). The implicit price of an attribute is computed as the parameter estimate on that attribute divided by the (negative of the) parameter estimate on price. The WTP value of a new wildfire protection program, which combines risk level i and loss level j within a public or private program, is computed as:

$$\mathrm{WTP_{ij}} = \left(V_{\mathrm{ij}}(\mathrm{p}) - V_{00}\right) \times \left(-1/\beta_p\right) \tag{9}$$

where $V_{\mathrm{ij}}(\mathrm{p})$ is the (indirect) utility of wildfire program p (public or private), V_{00} is the utility of the status quo and β_p is the parameter estimate on the price (cost) variable. The utility of the status quo is computed as:

$$V_{00} = \beta_1 \times \mathrm{risk}_0 + \beta_2 \times \mathrm{loss}_0 \tag{10}$$

where risk_0 (loss_0) is the risk (loss) level for the status quo and the β values are the parameter estimates for each of the attributes. The utility of a new wildfire protection program is:

$$V_{\mathrm{ij}}(\mathrm{p}) = \mathrm{ASC(p)} + \beta_1 \times \mathrm{risk_i} + \beta_2 \times \mathrm{loss_j} \tag{11}$$

where ASC(p) is the parameter estimate on the ASC for either the public or private program.

The specification of our empirical model allows us to estimate the actuarial value (AV) of a loss for any combination of wildfire risk and economic loss contained in our survey design:

$$\mathrm{AV_{ij}} = (\mathrm{risk_i}) \times \left(\mathrm{loss_j}\right) \tag{12}$$

which is simply the expected value loss associated with risk level i and loss level j. Using Eqn 12, we compute the actuarial value of (decadal) loss for the status quo (AV_{00}) as $(0.05) \times (\$100\,000) = \$5000$. The reduction in the expected value loss ($\mathrm{REVL_{ij}}$) due to any specific wildfire program provides an incentive to purchase that program, and is computed as the difference between actuarial values:

$$\mathrm{REVL_{ij}} = \mathrm{AV}_{00} - \mathrm{AV_{ij}} \tag{13}$$

These computations allow us to evaluate the risk preferences of survey respondents by computing the ratio of WTP for any specific wildfire protection program ($\mathrm{WTP_{ij}}$) to the reduction in expected value loss associated with that program ($\mathrm{REVL_{ij}}$).[J] In particular, risk preferences are risk-averse, risk-neutral or risk-seeking if $\mathrm{WTP_{ij}/REVL_{ij}}$ is greater than, equal to or less than unity. The EU model postulates that risk preferences are risk-averse, so we would expect that if this were the case then $\mathrm{WTP_{ij}/REVL_{ij}} > 1$. In contrast, prospect theory suggests that people hold risk-seeking preferences regarding losses so, if this were the case, we would anticipate that $\mathrm{WTP_{ij}/REVL_{ij}} < 1$.

Empirical results

Descriptive statistics for respondent characteristics used in the empirical models are shown in Table 1. The stratified sample included a substantial proportion of respondents with personal experience of the effects of wildfire (~43% of the sample). We note that nearly 15% of our respondents reported health effects from smoke produced by wildfires and ~35% reported that they had revised travel plans because of wildfires. Given that one-half of our stratified sample was drawn from communities identified as being at high risk for wildfires, it is surprising that only ~10% of respondents reported that they lived in an area that they perceived to be at high risk for wildfires. We also note that approximately three-quarters of respondents indicated that they had previously improved the defensible space on their property (trim lower branches on trees = 68%, remove vines from trees = 57%, remove branches over home = 39%, remove trees and flammable plants = 39%).

[J]This procedure is similar to that reported in McClelland and colleagues (1993) and in Ganderton and colleagues (2000). We note that although the relationship between $\mathrm{WTP_{ij}}$ and $\mathrm{REVL_{ij}}$ is slightly non-linear over the range of values we use in the experimental design, this slight non-linearity does not alter any of our conclusions. For simplicity, we present results for wildfire protection programs that reduce risk and loss by 50% from the status quo.

Table 2. Multinomial logit (MNL) estimates of homeowner preference parameters for wildfire hazard mitigation programs among survey respondents

The dependent variable is the alternative selected in the choice questions. Note: standard errors in parentheses. Probabilities are significant at *, $P < 0.10$; **, $P < 0.05$; ***, $P < 0.01$. n is the number of observations. McFadden R^2 is a goodness of fit measure that is based on estimates of the log-likelihood function including the intercept only *v*. the full model, and ranges between 0 (no explanatory power) and 1(perfect explanatory power)

Variable	MNL model	MNL model with personal experience
risk (%)	−0.074*** (0.02)	−0.032 (0.027)
risk × *personal experience*	–	−0.086*** (0.035)
loss ($1000)	−0.004*** (0.001)	−0.002** (0.001)
loss × *personal experience*	–	−0.004*** (0.001)
cost ($)	−0.0007*** (0.0001)	−0.0007*** (0.0001)
public program	0.034 (0.111)	0.047 (0.111)
public program × *high risk*	0.677*** (0.164)	0.695*** (0.164)
public program × *DS*	−0.162* (0.095)	−0.167* (0.095)
private program	−0.337*** (0.90)	−0.329*** (0.090)
private program × *high risk*	0.833*** (0.167)	0.838*** (0.168)
n	922	922
McFadden R^2	0.032	0.037

Table 3. Random parameter logit (RPL) model estimates of homeowner preference parameters for wildfire hazard mitigation programs among survey respondents, with random parameters estimated for risk and loss variables

The dependent variable is the alternative selected in the choice questions. Note: standard errors in parentheses. Probabilities are significant at *, $P < 0.10$; **, $P < 0.05$; ***, $P < 0.01$. n is the number of observations. McFadden R^2 is a goodness of fit measure that is based on estimates of the log-likelihood function including the intercept only *v*. the full model, and ranges between 0 (no explanatory power) and 1 (perfect explanatory power)

Variable	RPL model (mean)	RPL model (s.d.)	RPL model with personal experience (mean)	RPL model with personal experience (s.d.)
risk (%)	0.034 (0.046)	0.877*** (0.066)	0.119** (0.060)	0.871*** (0.066)
risk × *personal exp.*	–	–	−0.183** (0.082)	0.009 (0.343)
loss ($1000)	0.002 (0.002)	0.042*** (0.003)	0.007** (0.003)	0.042*** (0.003)
loss × *personal exp.*	–	–	−0.012*** (0.004)	0.002 (0.014)
cost ($)	–0.001*** (0.0001)	–	−0.001*** (0.0001)	–
public program	0.924*** (0.161)	–	0.935*** (0.161)	–
public pro. × *high risk*	1.100*** (0.308)	–	1.131*** (0.308)	–
public pro. × *DS*	−0.258*** (0.140)	–	−0.262* (0.140)	–
private program	0.352*** (0.228)	–	0.360*** (0.125)	–
private pro. × *high risk*	1.453*** (0.311)	–	1.475*** (0.311)	–
n	922	–	922	–
McFadden R^2	0.152	–	0.155	–

In the basic MNL model that does not include respondent heterogeneity, the parameter estimates on the *cost*, *risk* and *loss* variables were negative and statistically significant at the 0.01 level, all of which appears to be consistent with rational economic decision-making (Table 2). However, the parameter estimates on the *public program* and *private program* ASCs indicate that, on average, respondents favour the status quo (do nothing) alternative. Only respondents living in subjectively judged *high risk* areas prefer paying for new wildfire protection programs, and have a slightly higher WTP for public programs. Using Eqn 13, it is straightforward to compute that the reduction in expected value loss due to a 50% reduction in both wildfire risk and economic loss, relative to the status quo, is $3750 over the 10-year program period. Comparing the WTP estimates for wildfire protection programs that reduce wildfire risk and economic damage by 50% to the reduction in expected value loss, we see that preferences for wildfire protection programs for respondents living in neighbourhoods that they consider to be at *high risk* of wildfires are risk seeking (WTP/REVL = 0.40 for public programs and WTP/REVL = 0.21 for private programs).

Although the basic MNL model suggests that, on average, respondents are sensitive to *risk*, *loss* and *cost* attributes in making choices for wildfire protection programs, these results conceal significant heterogeneity across respondents. As demonstrated by the parameter estimates in the MNL model allowing heterogeneous preferences, it is only the respondents with *personal experience* of the effects of wildfire that consistently evaluated *risk–loss–cost* tradeoffs in a fully compensatory manner (Table 2). Other respondents apparently simplified decision-making by ignoring the risk attribute. Further, despite the fact that respondents with *prior experience* made sensible tradeoffs between program attributes, the WTP/REVL ratios for respondents with *personal experience* living in subjectively judged *high risk* areas indicate they held risk-seeking

Table 4. Latent class (LC) model estimates of homeowner preference parameters for wildfire hazard mitigation programs among survey respondents
The dependent variable is the alternative selected in the choice questions. Note: standard errors in parentheses. Probabilities are significant at *, $P < 0.10$; **, $P < 0.05$; ***, $P < 0.01$. n is the number of observations. McFadden R^2 is a goodness of fit measure that is based on estimates of the log-likelihood function including the intercept only *v.* the full model, and ranges between 0 (no explanatory power) and 1 (perfect explanatory power). For 'Covariates explaining latent class membership', in the 2-class model, Class 2 is the baseline and in the 3-class model, Class 3 is the baseline

Variable	2-class model		3-class model		
	Class 1	Class 2	Class 1	Class 2	Class 3
risk (%)	−0.002 (0.088)	−0.116*** (0.177)	0.007 (0.088)	−0.194** (0.058)	−0.173*** (0.026)
loss ($1000)	−0.009** (0.005)	−0.004*** (0.001)	−0.009** (0.004)	0.005* (0.003)	−0.008*** (0.001)
cost ($)	−0.003*** (0.001)	−0.001*** (0.0001)	−0.003*** (0.001)	0.0001 (0.0001)	−0.001*** (0.0001)
public program	−2.670*** (0.538)	2.231*** (0.114)	−2.562*** (0.519)	3.378*** (0.310))	1.364*** (0.163)
public program × high risk	1.559*** (0.437)	0.880** (0.365)	1.523*** (0.394)	28.427 (941745)	0.623 (0.411)
public program × DS	0.307 (0.457)	−0.122* (0.069)	0.234 (0.434)	−0.329 (0.233)	−0.044 (0.120)
private program	−2.563*** (0.401)	1.872*** (0.106)	−2.692*** (0.398)	0.832*** (0.302)	2.079*** (1.174)
private program × high risk	−0.610 (1.091)	1.173*** (0.372)	−0.317 (1.093)	27.130 (941745)	1.174*** (0.400)
Covariates explaining latent class membership					
Constant	−0.262*** (0.094)	–	0.311*** (0.117)	−0.287* (0.155)	–
personal experience	−0.590*** (0.146)	–	−0.820*** (0.168)	−0.540*** (0.216)	–
average class probability	0.374	0.626	0.373	0.231	0.397
n	922		922		
McFadden R^2	0.241		0.276		

preferences (ratios for a 50% decrease in both risk and economic loss were 0.46 and 0.39 for public and private programs). As might be anticipated, respondents with *personal experience* have higher WTP values for wildfire protection programs than the WTP values held by other respondents. We note that this result, which we found across all of the econometric models, is consistent with prior research indicating that WTP for environmental programs, estimated using contingent valuation, increases along with respondent experience (Cameron and Englin 1997).

The results of the RPL model specification confirm that respondents with *personal experience* of the effects of wildfire consistently made fully compensatory *risk–loss–cost* tradeoffs whereas other respondents did not (Table 3). Respondents without personal experience appeared to be confused about the risk and loss attributes, often exhibiting the wrong sign on parameter estimates associated with these attributes, and tended to anchor on the program labels. We note that, in the RPL model that includes *personal experience* in the model specification, the dispersion parameters on *risk* and *loss* are not significantly different than zero, indicating that the preferences of this subgroup were virtually fixed regarding these two attributes. Computing the WTP/REVL ratios for programs that reduce risk and loss by 50%, we found that respondents demonstrated risk-seeking preferences. For example, the ratio values for respondents with *personal experience* living in subjectively judged *high risk* areas were 0.64 and 0.58 for public and private wildfire protection programs (which are similar to, but somewhat higher than, the ratios computed using the results of the MNL model).

Although we specified the LC model by varying the number of classes between 2 and 5, the clearest results were obtained for the 2- and 3-class models. In the 2-class model, ~37% of respondents were classified in Class 1 (the Less Experienced class) and 63% are classified in Class 2 (the More Experienced class) (Table 4). Respondents in the Less Experienced class generally preferred the status quo to investing in a new wildfire protection program. Similar to previous models, only respondents with *personal experience* consistently made fully compensatory tradeoffs among *risk*, *loss* and *cost*. Further, WTP for public wildfire protection programs exceeded WTP for private programs for respondents in this group, and living in subjectively rated *high risk* areas further increased WTP. It is noteworthy that, for the More Experienced class, the WTP/REVL ratio for respondents with *personal experience* living in *high risk* areas indicated that risk preferences were neutral for public (WTP/REVL = 0.96) and private (WTP/REVL = 0.94) wildfire programs. This is likely due to the fact that in the LC models, ASC values are estimated specifically for respondents with More Experience.

The preferences of Class 1 (the Less Experienced class) in the 3-class model were similar to those in Class 1 in the 2-class model, and represent about the same proportion of the sample. Members in Class 2 ignore the *cost* attribute and appear to be 'yea-sayers' (the Yea-Saying class). Members of this class, who are less likely to have personal experience of the effects of wildfire, support public and private wildfire programs and yet their responses are not sensitive to variations in program *cost* (although they are sensitive to variations in *risk*)[K] Our results indicate that ~23% of respondents to our survey fall in this class, and that members of this class represent a subgroup of what was identified as the More Experienced class in the 2-class model.

Members in Class 3 (~40% of respondents) make fully compensatory tradeoffs among *cost*, *risk* and *loss* attributes, and respondents with *personal experience* of the effects of wildfire are most likely to be members of this group (the More

[K]We note that yea-saying has been previously identified in contingent valuation models (Holmes and Kramer 1995) and in choice experiments (Adamowicz *et al.* 2011).

Experienced class). The WTP/REVL ratios indicate that members of this class have moderately risk seeking preferences for public (WTP/REVL = 0.59) and private programs (WTP/REVL = 0.78) and, unlike prior models, indicate that WTP is higher for private programs than for public programs. Notably, we also found that preferences for private programs by members of this group who consider themselves to be living in a high fire risk area are moderately risk averse (WTP/REVL = 1.09). Again, we think this is largely due to the fact that ASC values are estimated specifically for respondents with More Experience.

Conclusions and discussion

The three econometric models used for analysis revealed several common themes in the data as well as some nuanced responses. We think that the most striking feature of our analyses, supported by each model that we estimated, is that only those respondents that had prior experience of the effects of wildfire consistently made fully compensatory tradeoffs between the *risk*, *loss* and *cost* of wildfire protection programs. Although we cannot unambiguously explain why respondents with prior experience attended more carefully to each of the wildfire program attributes, two alternative perspectives seem pertinent. The first perspective is based on the idea that prior valuation and choice experience mimics market behaviour and improves the accuracy of non-market valuation (Cummings Brookshire and Schulze 1986). The second perspective derives from a psychological, process-based view of decision-making for choices that are emotion-laden. In a foundational study, Luce and colleagues (1997) concluded that negative emotions induced by a choice problem contribute to more extensive processing of attributes (i.e. more attributes are considered) and that decision-making proceeds more by focusing on one attribute at a time (rather than the holistic assessment of alternatives) – conclusions entirely consistent with our results.[L] Similar conclusions were reported for the results of choice experiments designed to evaluate the effect of emotions on WTP decision-making for healthcare programs (Araña *et al.* 2008) and environmental protection programs (Araña and León 2009). In particular, these studies found that individuals exhibiting moderate emotional intensity more often make choices that are fully compensatory relative to individuals classified as having either extremely low or extremely high emotional intensity. As the threat of wildfire may induce emotional concerns, particularly among individuals that have previously experienced negative consequences of wildfire, this literature appears relevant and consistent with our results and deserves further study.

Admittedly, our choice experiment posed analytical challenges for respondents and the three econometric models helped to reveal some of the nuances of simplified decision-making among those respondents that did not use fully compensatory decision rules. The MNL model demonstrated that respondents lacking *prior experience* with wildfires focussed on tradeoffs between *loss* and *cost* and generally failed to consider *risk* in making decisions. This simplification strategy is consistent with the dual-focus model discussed by Ganderton and colleagues (2000) as well as the editing phase of decision-making inherent to prospect theory (Kahneman and Tversky 1979). This model also indicated that most respondents favoured the status quo over either a public or private wildfire protection program, and that only those respondents living in subjectively judged high fire risk areas would support new wildfire protection programs.

The RPL model, which faces fewer estimation restrictions than does the MNL model, revealed that many respondents appeared to be confused regarding the *risk* and *loss* levels presented in the experiment, as the dispersion parameter estimates on these attributes indicated a wrong sign for more than one-half of the respondents without *prior experience* of the effects of wildfire. The results also indicated that respondents simplified decision-making by focusing attention on the *cost* attribute and anchoring on the *public*/*private program* labels. The 3-class LC model identified a new class of respondents who were sensitive to *risk*, favoured the *public program* over the *private program*, but were not sensitive to program *cost*. These responses reflect another means of simplifying decisions (i.e. ignoring *cost* and *loss*) while expressing support for wildfire protection programs.

A second theme consistently revealed across the three econometric models is that WTP for wildfire protection programs was substantially greater for respondents who perceived that they lived in an area at high risk of wildfire. We note that whereas only ~10% of respondents reported that they lived in what they considered to be a high fire risk area, one-half of our sample was drawn from areas objectively assessed as being at high risk of wildfires. Developing a better understanding of the relationship between objective and subjective assessments of risk could help identify improved means of risk communication as well as identifying the aspects of fire prone landscapes that compel homeowners to judge that they are subject to high wildfire risk. Further, we note that the identification of locations at high risk of wildfire may be enhanced by methods for measuring wildfire consequences that represent local expert perceptions (Tutsch *et al.* 2010).

A third theme that was consistent across all three econometric models is that most of respondents made choices that reflected risk-seeking preferences regarding wildfire protection programs. Thus, although the studies by Winter and Fried (2001) and Talberth and colleagues (2006) appealed to expected utility theory to explain their results (which predicts that individuals are risk-averse), our results suggest that other theoretical models of decision-making under uncertainty need to be considered. This theme of risk-seeking preference is consistent with the prediction of prospect theory that people overweight a certain loss (the payment) relative to a probable loss (Kahneman and Tversky 1979).[M] Further, the prevalence of risk-seeking preferences regarding wildfire protection programs suggests the importance of keeping fuel reduction costs as low as possible

[L]These authors argued that negative emotion may act as signal that outcomes are important and thus provides a motivation to perform accurately.

[M]We note that ~96% of respondents had some level of homeowners' insurance, and that an insurance contract would likely cause respondents to lower their WTP for wildfire protection. However, responses to a follow-up question asking respondents to describe their rationale for the choices they made indicated that only ~2% of the respondents mentioned that existing insurance contracts influenced their choices.

while providing community members with believable estimates of wildfire risks and losses.

Overall, our results suggest that community members having prior experience with the consequences of wildfires in residential areas may be instrumental in communicating their views to other members of the community regarding fuel reduction measures. The fact that all three econometric models demonstrated that individuals with prior experience thought more carefully about *risk–loss–cost* tradeoffs, and that these individuals had higher WTP values for wildfire protection programs, suggests that they may be persuasive in articulating a well informed rationale for making investments today to protect their communities from potential effects of wildfire in the future. A potentially potent forum for developing support for community fuel reduction programs might then consist of a panel consisting of homeowners with well-informed views regarding the economic rationale for wildfire protection programs along with local fire management experts that have well-informed views regarding potential wildfire consequences.

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