# Does Personal Experience Affect Choice-Based Preferences for Wildfire Protection Programs[1,2]

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## 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. A phone-mail-phone survey was used to collect data from homeowners predominantly living in medium and high wildfire risk communities in Florida. We tested three hypotheses: (1) homeowner preferences for wildfire protection programs are risk averse, (2) past personal experience with wildfires increases homeowners' willingness to pay for protection programs, and (3) subjective perception of risk influences willingness to pay for protection programs. Preference heterogeneity among survey respondents was examined using two econometric models and risk preferences were evaluated by comparing willingness to pay for wildfire protection programs against expected monetary losses. The results showed that nearly all respondents had risk seeking preferences. Only respondents who had personal experience with wildfire impacts 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 wildfire impacts. Respondents living in neighborhoods that they viewed as being at high risk from wildfires also were willing to pay more than other respondents.

Keywords: Expected utility, heuristics, natural disasters, prospect theory, risk seeking, risk aversion

## Introduction

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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 neighborhoods in the United States has caused fire managers and policy-makers to emphasize 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 and others 2007). 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. In this paper we do this using a survey regarding homeowners willingness to pay (WTP) for private and public fire risk reduction programs.

One popular approach for evaluating WTP for environmental programs is the contingent valuation method (CVM), which asks people to respond to payment questions regarding hypothetical scenarios (Boyle 2003). This method has been applied to homeowner's WTP to reduce fire risk by Winter and Fried (2001) in Michigan and, recently Talberth and others (2006) of New Mexico homeowners

Loomis and others (2009) used a binomial choice response format to ask respondents whether or not they would vote in favor of fuel reduction programs in their state if it cost them a specified amount of money[6].

An alternative method for estimating WTP for environmental programs is based on a choice experiment (CE) 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.

## 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 (Shoemaker 1982). EU theory is based on the proposition that

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

people make choices so that expected utility is maximized, 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.

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). 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 behavior 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 very high to homeowners. It has been recognized 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 this idea, 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). 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 past personal experience of a catastrophe makes individuals more pessimistic regarding potentially catastrophic future events (Cohen and others 2008).

## Empirical methods

In this study, a CE was designed to estimate homeowner WTP for programs that reduce the risks (probabilities of damage) and economic losses. Recognizing 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 ($\varepsilon_{nj}$) components:

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

where $x_{jnk}$ is a vector of K explanatory variables observed by the analyst for alternative j and respondent n, $\beta_{nk}$ is a vector of preference parameters, and $\varepsilon_{jn}$ 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 $\Theta$ is:

$$P_n(j) = \exp(\mu\beta\chi_{jn}) / \Sigma_{j\varepsilon\theta}\exp(\mu\beta\chi_{jn}) \quad (2)$$

where $\mu$ is a scale parameter that is typically set equal to one. The RPL model is a generalized 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 $\beta_n$. These components allow the preference parameters for the $x_{jnk}$ explanatory variables to directly incorporate heterogeneity:

$$\beta_{nk} = \beta_k + \Gamma_{\upsilon nk} \quad (3)$$

where $\beta_k$ is the mean value for the $k^{th}$ preference parameter, $v_{nk}$ is a random variable with zero mean and variance equal to one, and $\Gamma$ 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 $\beta$, where the weights are determined by the density function $f(\beta|\theta)$ where $\theta$ is a parameter vector describing the distribution of $f(\bullet)$. Let $\pi_{nj}$ be the probability that an individual n chooses alternative j from set J, such that

$$\prod_{nj} = \oint L_{nj}(\beta\chi_j) f(\beta) d\beta \quad (4)$$

where

$$L_{nj}(\beta\chi_j) = \exp(\mu\beta\chi_{jn}) / \Sigma_{j=1} \exp(\mu\beta\chi_{jn}) \quad (5)$$

The function $f(\beta|\theta)$ can be simulated using random draws from various functional forms (Train 2002). The RPL model captures heterogeneity via a continuous probability distribution for preference parameters.

## 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 modified Krupnick and colleagues (2002) format by posing a situation where the risk of a home being damaged by a wildfire was represented, on a 1,000 square lattice, by a red square and the risk of being undamaged was represented by a white square. To simplify the conceptualization 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[7]. Our survey design varied the *risk* of private property damage during a 10 year period over five levels, from 1-5%, where 5% was the baseline risk associated with no new investments in wildfire protection programs[8]. Damages from wildfires were posed in terms of economic *loss* to property values with dollar amounts ranging from $10,000-$100,000. The *cost* of the wildfire risk reduction programs varied from $25-$1,000 for the public program and from $50-$1,000 for the private program.

[7] Because of space limitations figures are not include here, but you can see them in Holmes and others (2012; In print).
[8] We use *italics* to denote variables used in the empirical analysis.

The public program would include activities commonly used in Florida for managing vegetation and reducing fuels in forests and undeveloped areas near neighborhoods (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 empirical models for the public (*public_program*) and private (*private_program*) wildfire protection programs. We created a dummy variable to identify respondents who indicated that they perceive their home is located in a high (versus 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*). To test whether 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 using responses regarding whether or not people suffered smoke related illnesses because of wildfires, which was coded as unity if the response was affirmative and zero otherwise. Second, another dummy variable was created based on whether respondents altered their travel plans because of wildfires, 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.

## Experimental design and survey development

A completely randomized experimental design was used to construct the choice sets (Holmes and Adamowicz 2003). Potentially unique combinations of attribute levels were thus created for each choice set and respondent. Three alternatives were given in each choice set (Figure 1). 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 3 focus groups 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 pre-tested 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.

Figure 1 presents an example of the choice task given to the respondent in the survey.

| 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 | 1 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 of a choice question included in the homeowners survey to evaluate trade-offs between wildfire risk, damage and program costs.

## Survey sample

A stratified random sample of households living in single-family, owner-occupied residences was drawn from the population of households in Florida. Considering that people living in areas with 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 dialing. Then, households that were willing to participate in the survey were mailed a survey booklet. Within two weeks of receiving the booklet, a return 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

$$WTP_{ij} = (V_{ij}(p) - V_{00})*(-1/\beta_p) \quad (6)$$

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

$$V_{00} = \beta_1*risk_0 + \beta_2*loss_0 \quad (7)$$

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

$$V_{ij}(p) = ASC(p) + \beta_1*risk_i + \beta_2*loss_j \quad (8)$$

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:

$$AV_{ij} = (risk_i)*(loss_j) \quad (9)$$

which is simply the expected value loss associated with risk level i and loss level j. Using equation (9), we compute the actuarial value of (decadal) loss for the status quo ($AV_{00}$) as (0.05)*($100,000) = $5,000. The reduction in the expected value loss ($REVL_{ij}$) due to a specific wildfire program provides an incentive to purchase that program, and is computed as the difference between actuarial values:

$$REVL_{ij} = AV_{00} - AV_{ij} \quad (10)$$

These computations allow us to evaluate the risk preferences of survey respondents by computing the ratio of WTP for any specific wildfire protection

program ($WTP_{ij}$) to the reduction in expected value loss associated with that program ($REVL_{ij}$). In particular, risk preferences are risk averse, risk neutral, or risk seeking if $WTP_{ij} / REVL_{ij}$ is greater than, equal to, or less than unity, respectively. The EU model postulates that risk preferences are risk averse, so we would expect that if this were the case then $WTP_{ij} / REVL_{ij} > 1$. In contrast, prospect theory suggests that people hold risk seeking preferences regarding losses so, if this were the case; we would anticipate that $WTP_{ij} / REVL_{ij} < 1$.

## 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 wildfire impacts (about 43% of the sample). We note that nearly 15% of our respondents reported health effects from smoke produced by wildfires and roughly 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 about 10 percent of respondents reported that they lived in an area that they perceived to be at high risk for wildfires. We also note that roughly three-fourths of respondents indicated that they had previously improved the defensible space on their property.

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 favor 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 equation (10), it is straight-forward to compute that the reduction in expected value loss due to a 50 percent reduction in both wildfire risk and economic loss, relative to the status quo, is $3,750 over the 10-year program period. Comparing the WTP estimates for wildfire protection programs that reduce wildfire risk and economic damage by 50 percent to the reduction in expected value loss, we see that preferences for wildfire protection programs for respondents living in neighborhoods that they consider to be at *high risk* of wildfires are risk seeking or essentially WTP less than the expected losses (WTP/REVL = 0.40 for public programs and WTP/REVL = 0.21 for private programs.)

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

| Variable | Description | Mean (std. dev.) |
|---|---|---|
| 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 neighborhood; if Yes = 1; else = 0 | 0.10 (0.30) |

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 wildfire impacts that consistently evaluated *risk-loss-cost* trade-offs 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 trade-offs between program attributes, the WTP/REVL ratios for respondents with *personal experience* living in subjectively judged *high risk* areas indicate they held risk seeking preferences (WTP/REVL ratios for a 50% decrease in both risk and economic loss were 0.46 and 0.39 for public and private programs, respectively). 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, 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).

***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.*

| Variable | MNL model | MNL model w/ personal experience |
|---|---|---|
| *risk* (*%*) | -.074*** | -0.032 |
| | (0.02) | (0.027) |
| *risk *personal experience* | -- | -0.086*** |
| | | (0.035) |
| *loss* ($1,000) | -0.004*** | -0.002** |
| | (0.01) | (0.001) |
| *loss*personal experience* | -- | -0.004*** |
| | | (0.001) |
| *cost ($)* | -0.0007*** | -0.0007*** |
| | (0.0001) | (0.0001) |
| *public program* | 0.034 | 0.047 |
| | (0.111) | (0.111) |
| *public program*high risk* | 0.677*** | 0.695*** |
| | (0.164) | (0.164) |
| *public program*DS* | -0.162* | -0.167* |
| | (0.095) | (0.095) |
| *private program* | -0.337*** | -0.329*** |
| | (0.90) | (0.090) |
| *private program*high risk* | 0.833*** | 0.838*** |
| | (0.167) | (0.168) |
| N | 922 | 922 |
| McFadden $R^2$ | 0.032 | 0.037 |

Note: standard errors in parentheses. * indicates significance at the 0.10 level, ** indicates significance at the 0.05 level, *** indicates significance at the 0.01 level. N is the number of observations. McFadden $R^2$ is a goodness of fit measure that is based on estimates of thelog-likelihood function including the intercept only versus the full model, and ranges between 0 (no explanatory power) and 1(perfect explanatory power.)

The results of the RPL model specification confirm that respondents with *personal experience* of wildfire impacts consistently made fully compensatory *risk-loss-cost* trade-offs while 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 percent, 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, respectively (which are similar to, but somewhat higher than, the ratios computed using the results of the MNL model).

***Table 3***—*Random parameter logit model estimates of homeowner preference 712 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.*

| Variable | RPL model (mean) | RPL model (std. dev.) | RPL model w/ personal experience (mean) | RPL model w/ personal experience (std. dev.) |
|---|---|---|---|---|
| *risk* (%) | 0.034 | 0.877*** | 0.119** | 0.871*** |
| | (0.046) | (0.066) | (0.060) | (0.066) |
| *risk* personal exp.* | -- | -- | -0.183** | 0.009 |
| | | | (0.082) | (0.343) |
| *loss* ($1,000) | 0.002 | 0.042*** | 0.007** | 0.042*** |
| | (0.002) | (0.003) | (0.003) | (0.003) |
| *loss* personal exp.* | -- | -- | -0.012*** | 0.002 |
| | | | (0.004) | (0.014) |
| *cost ($)* | -.001*** | -- | -.001*** | -- |
| | (0.0001) | (0.0001) | | |
| *public program* | 0.924*** | -- | 0.935*** | -- |
| | (0.161) | (0.161) | | |
| *public pro.*high risk* | 1.100*** | -- | 1.131*** | -- |
| | (0.308) | (0.308) | | |
| *public pro.*DS* | -0.258*** | -- | -0.262* | -- |
| | (0.140) | | (0.140) | |
| *private program* | 0.352*** | -- | 0.360*** | -- |
| | (0.228) | | (0.125) | |
| *private pro.*high risk* | 1.453*** | -- | 1.475*** | -- |
| | (0.311) | | (0.311) | |
| N | 922 | -- | 922 | -- |
| McFadden $R^2$ | 0.152 | -- | 0.155 | -- |

Note: standard errors in parentheses. * indicates significance at the 0.10 level, ** indicates significance at the 0.05 level, *** indicates significance at the 0.01 level. 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 versus the full model, and ranges between 0 (no explanatory power) and 1(perfect explanatory power.)

## Conclusions and Discussion

The econometric models used for analysis revealed several common themes in the data as well as some nuanced responses. The most striking feature of our analyses, is that only those respondents that had prior experience of wildfire impacts consistently

made fully-compensatory trade-offs 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 is based on the idea that prior valuation and choice experience mimics market behavior and improves the accuracy of non-market valuation (Cummings and others 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 others (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.

Our choice experiment posed analytical challenges for respondents and the 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 focused on trade-offs 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 others (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 favored 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 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 wildfire impacts. The results also indicated that respondents simplified decision-making by focusing attention on the *cost* attribute and anchoring on the *public/ private program* labels.

A second theme consistently revealed across 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 about 10 percent 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.

A third theme consistent across all econometric models is that the vast majority of respondents made choices that reflected risk seeking preferences or were willing to pay less than the expected loss for the wildfire protection programs. Thus, while the studies by Winter and Fried (2001) and Talberth and others (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). Further, the prevalence of risk seeking preferences regarding wildfire protection programs suggests the importance of keeping fuel reduction costs as low as possible 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 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 wildfire impacts in the future.

## Summary

Results from a stated preference survey indicate that most homeowners in Florida living in fire-prone communities tend to under-invest in programs designed to reduce wildfire risk. Willingness to pay for wildfire protection programs increases for homeowners who have prior personal experience with the consequences of wildfire. Therefore, these people may be influential in encouraging other community members to invest in wildfire protection.

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