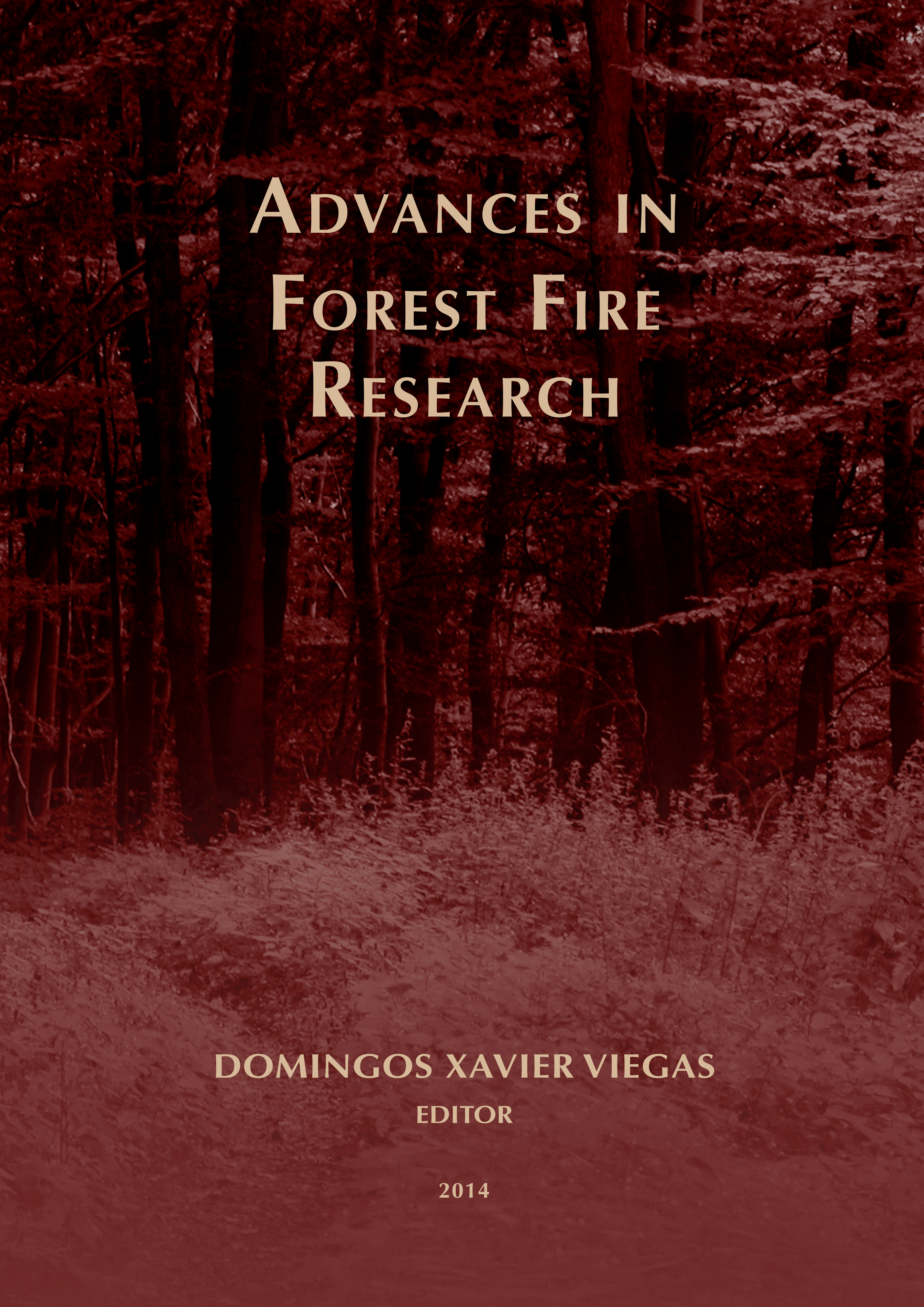

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Identifying risk preferences among wildfire managers and the consequences for incident management outcomes

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Abstract

Management of wildfire incidents involves trade-offs over risks to firefighting personnel, private property and infrastructure, ecological values, public exposure to harm, and the costs of management. Trade-offs, non-linear probability weighting, and risk preferences among wildfire managers are investigated using a multi-attribute lottery choice experiment. The survey-based experiment asks managers to make strategic choices with varying levels of risk to aviation personnel, property damage, and suppression costs. A latent-class model is estimated to identify two classes of respondents with varying degrees of non-linear probability weighting. Differences between the two classes, explained by differences in educational attainment, suggest that expected outcomes of wildfire can vary depending on risk preferences and individual characteristics of managers.

Keywords*: risk management, decision biases, wildfire outcomes, lottery experiment*

1. Introduction

Wildfire incidents present a complex risk management environment. Wildfire managers must often make decisions that balance multiple potential outcomes, long-term and short-term risks, and social and political pressures. However, relatively little attention has been paid to how differences in risk preferences among managers affect management decisions and wildfire outcomes. Risk-related decision biases – including risk aversion, probability weighting, and status quo bias, among others – have been demonstrated in a wide variety of decision environments, including wildfire management (Maguire and Albright 2005; Wilson *et al*. 2011; Wibbenmeyer *et al*. 2013). This paper builds on previous work by investigating the role of heterogeneity of risk preferences in determining outcomes on individual incidents and the fire management program.

Of primary interest in this paper is the degree to which risk preferences vary within the population of fire managers. Previous research has established that probability weighting, risk aversion, and information framing drive choices of fire managers that depart significantly from an expected loss-minimization baseline. However, the degree to which managers exhibit risk biases may vary in the population. Differences in risk preferences within the target population can have implications for the expected outcomes of strategic choices made by managers and the extent that choices depart from expected loss-minimizing choices.

Risk preferences are examined using insights from a survey-based experiment administered to Federal wildfire managers in the United States in 2012. The experiment presented managers with a series of strategy choices to respond to a hypothetical wildfire scenario. A random utility model of risky strategic choices is adapted to allow for non-linear probability weighting and risk preferences (e.g., risk aversion). We estimate a latent class model of risk preferences to distinguish between different types (or classes) of respondents in the sample. Latent class models are a way to describe heterogeneity in the sample by identifying different response patterns (usually by estimating some unique parameters for each class) and the factors that are associated with respondents being members of each class

(Greene and Hensher 2013). In this application reported educational attainment is used to identify groups of managers that exhibit varying degrees of risk biases.

2. A survey-based lottery choice experiment

The primary method used to estimate risk aversion and probability weighting parameters is a multiple-attribute lottery choice experiment. Single-attribute lottery choice (also called multiple price list) experiments have been used to identify risk preferences in a variety of settings, e.g., Holt and Laury (2002) and Taylor (2013). In this study, managers are presented with a series of multi-attribute lotteries; respondents are asked to select strategies that reflect potential responses to a hypothetical wildfire scenario.

Each choice set (i.e., lottery) offered a relatively ``safe" strategy and a relatively ``risky" strategy. Both strategies are defined by potential good and bad outcomes that occur with probabilities that vary in the experimental design. The safe strategy represents a situation with moderate use of suppression resources to contain the hypothetical wildfire. The risky strategy involves monitoring the fire with minimal commitment of suppression resources; such strategies are used when potential values at risk are low or favorable conditions are expected to continue for the foreseeable future. As in lottery experiments with financial outcomes, the risky strategy yields good outcomes that are better than the good outcomes in the safe strategy, but bad outcomes that are worse than the bad outcomes in the safe strategy.

The lottery choices require respondents to make tradeoffs over three outcome attributes that are hypothesized to enter the fire manager utility function: Exposure of aviation personnel to the risk of a fatality, damage to private property, and total suppression expenditures for the incident. Potential outcomes for each of the attributes under both the safe and risky strategies are given in table 1. Attribute levels for the good and bad outcomes under the safe strategy and good outcomes under the risky strategy were held constant across all of the choice sets seen by each respondent. The attribute levels in the risky strategy--bad outcome were varied using an experimental design to test risk preferences of respondents across a range of utility values.

Table 1. Attribute levels used in the experimental design

	Safe strategy		Risky strategy[a]		
Attribute	Good outcome	Bad outcome	Good outcome	Bad outcome – low	Bad outcome – high
Aviation exposure	50 hours	75 hours	10 hours	300 hours	1,200 hours
Private property damage	$600,000	$1.25 mil.	$700,000	$3 mil.	$14 mil.
Suppression cost	$300,000	$500,000	$25,000	$2 mil.	$12.5 mil.

[a] Each attribute has two potential bad outcomes under the risky strategy. The Risky-Bad outcomes were varied systematically among the choice sets using a full-factorial design.

To identify how managers respond to lotteries over a range of probabilities, the probability (p) that the good outcome obtains is varied in the experimental design, taking six different values: 0.7, 0.85, 0.9, 0.95, 0.98, and 0.995. Respondents saw probability information displayed as both a percentage (e.g., a 70% chance the good outcome results) and as a frequency (e.g., 700 out of 1,000 fires where the good outcome results).

The risky strategy--bad outcome attributes (two for each of the three attributes) and the outcome probabilities are combined to form choice sets using a 2x2x2x6 full-factorial design, resulting in 48 unique choice sets. A framing experiment was also incorporated into the experimental design. Half of the sample saw the aviation exposure attribute expressed in expected fatalities per 1,000 incidents (the treatment group) rather than hours of aviation use (the control group). Based on historical accident and fatality rates for the U.S. Forest Service, the aviation exposure attribute was converted to a fatality rate using an average of 4.801 fatalities for every 100,000 flight hours (USDA Forest Service 2010). The econometric models used to analyse the data are estimated separately on the control group sample and the treatment group sample.

The choice sets were blocked into six blocks of eight choice sets, with potential respondents randomly assigned to one of the six blocks. Details of the survey administration can be found in Wibbenmeyer *et al*. (2012). Figure 1 displays sample choice sets for the control and treatment groups.

Strategy A		
90.0%	Aviation Exposure	50 hours
	Private property damage	$600,000
900 of 1000 wildfires	Suppression cost	$300,000
10.0%	Aviation Exposure	75 hours
	Private property damage	$1.25 million
100 of 1000 wildfires	Suppression cost	$500,000

Strategy B		
90.0%	Aviation Exposure	10 hours
	Private property damage	$700,000
900 of 1000 wildfires	Suppression cost	$25,000
10.0%	Aviation Exposure	1200 hours
	Private property damage	$14 million
100 of 1000 wildfires	Suppression cost	$12.5 million

A: Control frame

Strategy A		
90.0%	Aviation Exposure	2.4 deaths in 1000 fires
	Private property damage	$600,000
900 of 1000 wildfires	Suppression cost	$300,000
10.0%	Aviation Exposure	3.6 deaths in 1000 fires
	Private property damage	$1.25 million
100 of 1000 wildfires	Suppression cost	$500,000

Strategy B		
90.0%	Aviation Exposure	0.5 deaths in 1000 fires
	Private property damage	$700,000
900 of 1000 wildfires	Suppression cost	$25,000
10.0%	Aviation Exposure	58 deaths in 1000 fires
	Private property damage	$14 million
100 of 1000 wildfires	Suppression cost	$12.5 million

B: Treatment frame

Figure 1. Sample choice sets for the control (A) and treatment (B) frames

3. Econometric specifications

Analysis of the observed lottery choices is conducted using a modified version of a random utility conditional logit model. In this case, assuming that the random component of choices has a type I extreme value distribution (Train 2009, ch.3), the conditional logit model expresses the probability of selecting the "safe" strategy over the "risky" strategy as:

$$(1) \qquad Pr(Safe) = \frac{e^{V_S}}{e^{V_S}+e^{V_R}}$$

where V_S and V_R represent the deterministic component of utility associated with the "safe" and "risky" strategies, respectively. The utility functions are specified using a linear-in-attributes form, modified to accommodate probability weighting and risk preferences. Similar recent examples of this approach include Hensher *et al*. (2011), van Houtvan *et al*. (2011), Sun *et al*. (2012) and Wibbenmeyer *et al*. (2013). Probability weighting is specified using a single-parameter non-linear weighting function of p drawn from Prelec (1998): $\pi(p) = exp - (-\ln p)^{\gamma}$. Risk preferences are specified using a constant relative risk aversion form as in Hensher *et al*. (2011). Incorporating probability weighting and risk preferences results in the following utility function for strategy m, which is defined by the good (G) and bad (B) potential outcomes, attribute preference parameters (β_k), the probability weighting parameter (γ), and the risk preferences parameter (α):

$$(2) \qquad V_m = \pi(p_G)\left(\frac{1}{1-\alpha}\right)(\beta_{AE}AE_{mG}^{1-\alpha} + \beta_D D_{mG}^{1-\alpha} + \beta_C C_{mG}^{1-\alpha}) + \big(1 - \pi(p_G)\big)\left(\frac{1}{1-\alpha}\right)(\beta_{AE}AE_{mB}^{1-\alpha} + \beta_D D_{mB}^{1-\alpha} + \beta_C C_{mB}^{1-\alpha})$$

where AE is the aviation exposure attribute, D is the property damage attribute, and C is the suppression cost attribute.

To examine heterogeneity among managers, a latent class model is developed following the approach described in Sun *et al*. (2012) and Greene and Hensher (2003). The latent class model assumes that two distinct classes of strategy choosers exist in the population of managers. The likelihood of belonging to one or the other class is determined by reported educational attainment.[1] The probability that individual i is a member of class q is specified as a conditional logit:

$$(3) \quad H_{iq} = \frac{e^{Z'_i\Theta_q}}{e^{Z'_i\Theta_1}+e^{Z'_i\Theta_2}}, \Theta_1 = 0$$

where Z is a vector of educational attainment indicator variables, and Θ is a vector of parameters that describe the relationship between Z and the likelihood of membership in class q. Θ_1 (corresponding to class 1) is normalized to zero to identify the parameter vector.

Separate choice probabilities (equation 1) are specified for each class. In this application, the choice probability specifications include common attribute preference parameters (βs) and risk preferences parameter (α), but the probability weighting parameter is allowed to vary between the two classes (γ_1 and γ_2 for class 1 and 2, respectively). Although it is possible that other parameters besides those in the probability weighting function vary between classes, holding the other parameters constant

[1] A variety of variables and question responses was used to test class membership probabilities. Educational attainment provided the best fit of candidate regressions.

allows us to isolate differences among managers in responses to probabilities and limits the complexity of the maximum likelihood estimation.[1]

4. Results

Results from the latent class model suggest that there are at least two classes of respondents in the sample, and that the classes respond to probability differences in distinct ways. Two sets of results are presented in table 2, one each for the control group and the treatment group.

4.1. Latent class model estimates

For both the control group (who saw the aviation exposure attribute expressed as hours of aviation use) and the treatment group (who saw the aviation exposure attribute expressed as expected fatalities), one class exhibited severe probability weighting ($\gamma_1 < 0.2$) and the other class exhibited significant but more moderate probability weighting ($\gamma_2 \sim 0.7$). This suggests that some differences in strategic choices observed in the respondent sample can be attributed to variations in the sample in how managers weight different outcome probabilities.

Table 2. Latent class model parameter estimates by treatment frame

Attribute/parameter	Control frame	Treatment frame
Aviation exposure (flight hours or fatality rate)	-.878***	-2.22***
Private property damage ($)	-1.01***	-.875***
Suppression costs ($)	-.590***	-.192*
Θ_2 (class 2 membership)	-1.08**	-2.06**
Some college education	.906	2.26**
Bachelor's degree	1.76***	2.68***
Graduate degree	1.65***	2.72***
γ_1 (prob. weighting for class 1)	.165***	.137***
γ_2 (prob. weighting for class 2)	.703***	.672***
α (risk preference)	1.02***	.951***
Choice obs (N)	4,097	4,059
Number of respondents	516	511
ln(L)	-2,241	-2,179
AIC	4,501	4,307

*, **, and *** indicate significance at the 90%, 95%, and 99% level respectively.

The observed pattern of probability weighting indicates that managers over-weight low probabilities and under-weight high probabilities. In the case of the extreme probability weighting class (class 1), estimates imply that some managers perceive outcome probabilities to be in the 0.3 to 0.5 range over a large portion of the probability spectrum. Over-weighting low probabilities has the consequence of encouraging managers to avoid strategies with low-likelihood bad outcomes more than they would if they chose according to expected loss minimization, i.e., they appear to avoid taking "good bets" on

[1] The models that allowed additional parameters to vary between the classes, and models with more than two classes, exhibited significant difficulty with maximum likelihood convergence.

low-likelihood bad outcomes. Conversely, under-weighting high probabilities encourages managers to avoid good bets with high-likelihood good outcomes.

Model estimates also show that educational attainment helps explain the likelihood of a respondent belonging to either class. Compared to respondents with a high school diploma or less education, those with a bachelor's or graduate degree are more likely to be members of class 2 (the moderate probability weighting class). For the treatment group, having any amount of college education or more is associated with class 2 membership. This suggests that greater educational attainment is associated with strategy decisions that are more closely aligned with expected loss minimization (at least in terms of probability weighting). However, we cannot assess from the results whether this represents a causal mechanism (i.e., obtaining more education results in less severe probability weighting in decision making), or whether educational attainment is associated with other unobserved characteristics that may drive differences in probability weighting.

4.2. Expected attribute outcomes by educational attainment

The lottery choice experiment was designed such that the (hypothetical) outcomes for each attribute that result from a choice are determined probabilistically. Further, the experimental design and attribute levels were calibrated to ensure that for some lotteries the "safe" option will result in lower expected attribute outcomes, whereas for other lotteries the "risky" option will result in lower expected attribute outcomes. To examine the potential consequences of probability weighting and risk preferences on expected attribute outcomes, we calculated the expected outcomes under an expected loss minimization (ELM) choice pattern (with linear probability weighting and risk neutrality). These were then compared to expected outcomes calculated based on likely strategy choices for the estimated latent class model.

Table 3 displays expected attribute outcomes under ELM choices and under estimated latent class model choices for the control and treatment groups. Under modelled choices, expected outcomes are calculated for each educational attainment category, with choice probabilities for each class weighted by each respondent's likelihood of class 2 membership (note that under ELM there is no difference between classes because all individuals are assumed to exhibit no probability weighting). Attribute preferences (which in part determine choice probabilities) are assumed to be the same for ELM choices and latent class model choices.

Table 3. Average expected attribute outcomes under ELM and modelled choices, by educational attainment.

	Control frame	Treatment frame
Expected loss minimization choices		
Aviation exposure (fatalities per 1,000 fires)	2.6	2.7
Property damage (mil. $)	.785	.815
Suppression costs (mil. $)	.339	.388
Modelled choices		
HS diploma or less		
Aviation exposure (fatalities per 1,000 fires)	4.1	3.3
Property damage (mil. $)	1.25	1.02
Suppression costs (mil. $)	.659	.514
Some college education		
Aviation exposure (fatalities per 1,000 fires)	3.9	3.3
Property damage (mil. $)	1.16	1.06
Suppression costs (mil. $)	.640	.535
Bachelor's degree		

Aviation exposure (fatalities per 1,000 fires)	3.8	3.2
Property damage (mil. $)	1.10	1.05
Suppression costs (mil. $)	.585	.518
Graduate degree		
Aviation exposure (fatalities per 1,000 fires)	3.6	3.1
Property damage (mil. $)	1.12	1.06
Suppression costs (mil. $)	.639	.545

For both the control and treatment groups, modelled choices result in an increase in the number of expected fatalities of between 40 and 60 percent (which represents approximately an additional fatality per 1,000 fires) compared with ELM choices. The amount of expected property damage is also higher under modelled choices by a similar factor, and expected suppression expenditures are higher by between 50 and 100 percent.

The differences in probability weighting between the two classes have implications for expected attribute outcomes. For those respondents with the greatest likelihood of membership in the moderate probability weighting class (class 2), the differences in expected outcomes between ELM and modelled choices are smaller. In the control frame, greater educational attainment in the sample is associated with attribute outcomes that are closer to expected loss minimization, i.e., fewer expected fatalities, less property damage, and less suppression expenditures. In the treatment frame, where the negative consequences of aviation use were highlighted, educational attainment is only associated with reduced expected aviation fatalities. This may be due to respondents in the treatment group exhibiting a greater preference for reducing aviation fatalities than property damage or suppression costs relative to the control group.

5. Conclusion

Responding to wildfire incidents requires careful consideration of risks and potential outcomes associated with available strategies. This paper has examined how Federal wildfire managers respond to risk by observing hypothetical choices over strategies that involve risk to fire outcomes. An econometric analysis of a survey-based lottery choice experiment indicates that respondents tend to be risk averse and exhibit non-linear weighting of outcome probabilities. Specifically, respondents on average over-weighted low probabilities and under-weighted high probabilities relative to linear probability weights.

Using a latent class model of strategy choices, we discovered that at least two classes of respondents exist in the sample. One class is characterized by extreme non-linear probability weighting, and the other class exhibits non-linear but more moderate probability weighting. The likelihood of class membership is significantly associated with educational attainment; respondents with more education are more likely to be members of the moderate probability weighting class.

Probability weighting, risk aversion, and latent classes have implications for the expected outcomes of the hypothetical wildfires respondents were asked to manage. Compared to an expected loss minimization strategy baseline (i.e., linear probability weighting and risk neutrality), respondents made decisions that on average resulted in greater expected aviation fatalities, property damage, and suppression costs. That is, risk and decision biases tend to result in increased losses to outcome attributes thought to be important to fire managers when they make strategic decisions. However, a portion of the respondent sample exhibited less-severe biases, which tends to mitigate these losses.

It is important to note that the results were obtained using a hypothetical choice scenario, and it is unclear how the quantitative results would apply to real-world fire management scenarios. However, the results suggest that how managers respond to risk can be an important determinant of fire outcomes. Also, a better understanding of heterogeneity of risk preferences among managers could assist training and after-action review efforts to improve risk management skills. Although there is not currently a reliable way to generate empirical probabilities of strategy outcomes, future research would benefit from a focus on more realistic management scenarios, particularly those that incorporate a temporal dimension of strategic decision making.

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