Risk Analysis, Vol. 35, No. 10, 2015 DOI: 10.1111/risa.12457

Risk Preferences, Probability Weighting, and Strategy Tradeoffs in Wildfire Management

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Wildfires present a complex applied risk management environment, but relatively little attention has been paid to behavioral and cognitive responses to risk among public agency wildfire managers. This study investigates responses to risk, including probability weighting and risk aversion, in a wildfire management context using a survey-based experiment administered to federal wildfire managers. Respondents were presented with a multiattribute lottery-choice experiment where each lottery is defined by three outcome attributes: expenditures for fire suppression, damage to private property, and exposure of firefighters to the risk of aviation-related fatalities. Respondents choose one of two strategies, each of which includes "good" (low cost/low damage) and "bad" (high cost/high damage) outcomes that occur with varying probabilities. The choice task also incorporates an information framing experiment to test whether information about fatality risk to firefighters alters managers' responses to risk. Results suggest that managers exhibit risk aversion and nonlinear probability weighting, which can result in choices that do not minimize expected expenditures, property damage, or firefighter exposure. Information framing tends to result in choices that reduce the risk of aviation fatalities, but exacerbates nonlinear probability weighting.

KEY WORDS: Lottery-choice experiment; probability weighting; risk aversion; risk preferences; wildfire management

1. INTRODUCTION

Wildfires present a complex applied risk management environment. Public managers of wildfires are tasked with assessing and responding to incident risks and making a series of strategic decisions that affect homeowners, residents in smoke-affected communities, forest ecosystems, and firefighters in harm's way. Wildfire management is also an expensive endeavor; over the past 10 years, the U.S. Forest Service has spent about $10.2 billion (in 2012 dollars) on wildfire suppression. Institutional incentives and sociopolitical factors are likely important determinants of decisions and costs,(1,2) but relatively little attention has been paid to behavioral and cognitive responses to risk among public agency managers.

Similar to other public risk management problems, such as disease pandemics, terrorist threats, and some natural disasters, wildfire managers must make decisions over risk tradeoffs: fire outcomes are defined along multiple dimensions that managers weigh during a fire (e.g., property loss, ecosystem health, public, and firefighter safety). Decisions that managers make in a risky environment are also likely subject to the same biases and behavioral effects that can lead to suboptimal outcomes for individuals.(3,4)

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This study investigates a type of public risk management problem defined by tradeoffs among multiple attributes at risk and the potential of managers to affect the likelihood and severity of outcomes. Of primary interest is how public managers make strategic choices in response to risk and tradeoffs over potential outcomes, and the degree to which these choices result in suboptimal outcomes from a public perspective. Building on previous research on wildfire manager decisions,[5,6] a survey-based experiment is used to elicit choices among strategies by federal wildfire managers in a hypothetical wildfire scenario. A random utility model (RUM) is adapted to allow for nonlinear probability weighting and risk preferences (e.g., risk aversion). In addition to illustrating the risk preferences and attitudes of managers, empirical results can shed light on the factors that are related to managers' risk decisions, and how information can be presented to managers to alter choices and outcomes.

2. A NONEXPECTED UTILITY MODEL OF WILDFIRE MANAGEMENT DECISIONS

Wildfire management is a complex decision environment where managers must make strategic decisions that balance multiple objectives with potential outcomes subject to risk.[3] Although wildfire incidents over time and space can share similar characteristics, each incident presents a unique set of challenges that a manager must negotiate. In short, there is no "one-size-fits-all" approach to managing wildfires, and no playbook that can accommodate all wildfire scenarios. This type of environment is characterized by aspects of stability and high validity (e.g., during early stages of fire control efforts), where managers can become skilled judges and decisionmakers, and aspects of uncertainty and low validity (e.g., during large and complex incidents), which hinders the development of skilled intuitions among decisionmakers.[4(7)]

The null hypothesis in this study is that managers make decisions that avoid common risk biases by being coolly analytical and not relying on the affective information processing described by Epstein[(8)] and Slovic *et al.*[(9)] Under this hypothesis fires are managed to minimize the total expected losses to valuable assets and other attributes at risk (e.g., infrastructure, ecological functions, and human safety).[5] Models of wildfire management with risk describe efficient strategies as those that minimize the sum of expected suppression expenditures and net value change to resources.[(10–13)] An underlying assumption for efficient management is that managers are risk neutral and unbiased in their response to known and objective outcome probabilities.

To model manager decisions under risk, suppose that managers derive utility from a set of wildfire outcomes, e.g., consistent with utility-theoretic models of efficient wildfire management.[(14)] The manager utility function may represent personal or professional preferences, and may or may not correspond to the public's preferences over potential wildfire outcomes.[6] No assumption is made about how managers form their preferences, only that their preferences can be represented by a well-behaved utility function. The deterministic component of the utility of a given outcome j is defined as:

$$v_j = v(\mathbf{x}_j|\beta), \quad (1)$$

where $\mathbf{x}_j$ is a vector of attributes of outcome j and β is a vector of utility function parameters that describe relative preferences for each of the attributes in $\mathbf{x}$.

The outcomes of a wildfire are, of course, not generally known in advance with certainty. Managers must decide which strategy to pursue knowing that multiple potential outcomes may occur with varying probabilities. A strategy utility function is adapted from cumulative prospect theory,[(15)] where the utility a manager expects to receive from choosing management strategy m is a weighted sum of the utility of all potential outcomes, or:

$$V_m = \sum_j \pi(p_j)v(\mathbf{x}_j|\beta), \quad (2)$$

[3] This study is focused primarily on risk where potential outcomes and the likelihood that they occur are known. In a wildfire management context, focusing on risk is consistent with decision support tools (e.g., simulated burn probability maps) that present information in terms of probabilistic outcomes. Although uncertainty (where potential outcomes or their likelihood are unknown) is assuredly part of the wildfire decision environment, it is beyond the scope of this study.

[4] Thanks to an anonymous reviewer for making this connection.

[5] The effects of wildfire are described here to be solely in the loss domain, which simplifies the manager's objective function of minimizing losses. Fire can have beneficial effects, but a study of manager preferences over fire outcomes in different domains is left for future research.

[6] In fact, managers appear to be able to distinguish between their personal preferences and the preferences that best align with community, leadership and political expectations; the differences in these preferences can significantly alter management choices and wildfire outcomes.[(6)]

where $\pi(p_j)$ describes decision weights as a function of the $j = 1, \ldots, J$ probabilities ($\sum_j p_j = 1$) that each outcome is realized, and $v(\mathbf{x}_j|\beta)$ is the utility of the jth outcome.

Preferences over strategies are related to choices by incorporating risk within an RUM of choice over multiattribute goods. The basic RUM is the basis for a wide range of empirical choice studies (see McFadden,[16] Louviere *et al.*,[17] and Train[18] for the basic theoretical development). In this case, managers select the strategy that yields the highest utility, defined as the sum of deterministic strategy utility (Equation (2)) and an unobserved random component ϵ. That is, managers make a decision Y to choose strategy m using the following decision rule:

$$Y = m \text{ if } V_m + \epsilon > V_n + \epsilon \quad \forall n \neq m. \tag{3}$$

Strategy choices that minimize expected losses from wildfires imply linear responses to changes in outcome probabilities—and specifically that $\pi(p_j) = p_j$—and linear-in-parameters responses to changes in potential outcomes. That is, under expected loss minimization (ELM), the strategy utility function reduces to:

$$ELM_m = \sum_j p_j \left(\sum_k \beta_k' x_{jk} \right), \tag{4}$$

where $\sum_k \beta_k' x_{jk}$ is the effect on utility of losses to each of the k attributes weighted by the vector of utility function parameters β.[7]

The null hypothesis for this study is that wildfire manager decisions are consistent with Equation (4). Two alternative hypotheses are investigated: nonlinear probability weighting, where $\pi(p_j) \neq p_j$, and nonneutral risk preferences over outcomes (e.g., risk aversion or risk seeking). Nonlinear probability weighting implies that for a given potential loss in utility, changes in the probability of an outcome are valued differently along the probability spectrum (i.e., $\partial V_m/\partial p_j \neq v(\mathbf{x}_j|\beta)$, $\partial^2 V_m/\partial p_j^2 \neq 0$). Nonneutral risk preferences imply that for a given probability of an outcome, the marginal value of a change in potential loss is nonconstant across the range of potential losses (i.e., $\partial V_m/\partial x_{jk} \neq \beta_k$, $\partial^2 V_m/\partial x_{jk}^2 \neq 0$).

[7] The linear-in-parameters utility function also corresponds to the functional form of utility functions used for empirical analysis of discrete choice; see Train.[18] An underlying assumption when using the linear form is that utility is additively separable in the attributes.

2.1. Effects of Framing on Manager Choices

It is well established that decisions involving risk are governed by several factors other than analytical assessments of outcome probabilities and levels. This is also likely true for the population of wildfire managers in particular.[3,4] Wildfire managers have access to a wide and increasingly detailed array of information about the incidents they manage, including qualitative, quantitative, and geospatial information.[19] Decision support systems are also becoming a key tool for implementing a risk management decision framework for wildfire managers.[1] An additional hypothesis of this study is that the way relevant information is presented about fire outcomes—information framing—can affect how managers perceive risky situations and make decisions.

Framing effects on decisions have been shown to result in violations of the axioms of purely rational choice,[20] and affect decisionmakers' degree of risk aversion in lottery choices.[21] Information framing may change the reference point for outcomes (e.g., the effect on decisions of an equivalent "cash discount" vs. "credit card surcharge" described by Tversky and Kahneman[20]), and manipulating the affective response to information presented to respondents can alter judgments about risks and benefits.[22] If people are able to accurately perceive the risks and consequences of different decisions, then equivalent outcomes described in different ways would have no effect on choices.

The null hypothesis that framing has no effect on decisions is investigated here in the context of firefighter safety. Safety has become a high priority for the Forest Service,[23] with an explicit goal of eliminating workplace-related fatalities among agency employees. With respect to wildfire management, a goal is to avoid fatalities and injuries to firefighters by making strategic decisions that balance the exposure of firefighters to risk, risks to valuable assets, and the probability of strategy success.[24] In order to achieve this goal, it would be helpful to know whether information presented to fire managers can encourage strategic decisions that result in reduced firefighter exposure, and what the consequences of those decisions are for other fire outcomes.

In this case, framing is investigated by manipulating information about firefighter exposure to risk to prime respondents' affective processing of strategic choices. Affective content can influence the emotional connection decisionmakers have for potential outcomes.[25,26] If this exists for fire managers, it is expected that an informational frame designed to prime affective processing for firefighter exposure would encourage managers to exhibit a higher value for losses (i.e., through the relative magnitudes in the β vector) and a lower willingness to accept risk of losses to that attribute (i.e., more severe probability weighting and risk aversion).

3. A MULTIATTRIBUTE LOTTERY EXPERIMENT

To test whether wildfire managers exhibit decision making consistent with ELM, a survey-based experiment was conducted to observe strategy choices in a stylized wildfire environment. The experiment is based on lottery-choice experiments used in a variety of contexts (e.g., Holt and Laury[27]) to estimate risk aversion and probability weighting parameters in an experimental sample. In this study, managers are presented with a series of multiattribute 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 human safety and valuable assets are not threatened by the fire or favorable weather conditions are expected to continue for the foreseeable future.

For both strategies, the good outcome occurs with probability p, and the bad outcome occurs with a probability of $1 - p$. The bad outcome represents a potential change in conditions that results in more extreme fire activity, greater threat to human safety and damage to valuable assets, and greater suppression efforts needed to contain the fire. 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.

Three attributes define the outcomes for each strategy: exposure of aviation personnel to risk, damage to private property, and total suppression expenditures for the incident. These attributes comprise the set of factors that are hypothesized to enter the strategy utility function (i.e., are included in the $\mathbf{x}_j$ vector). Potential outcomes for each of the attributes under both the safe and risky strategies are given in Table I. The different attribute levels between the two strategies identify the relative preferences that respondents have for each attribute when choosing a strategy. 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.

A primary question addressed in this study is whether managers respond nonlinearly to changes in outcome probabilities when making wildfire strategy decisions (i.e., that respondents under- or overweight some outcome probabilities relative to decisions that minimize expected losses). To identify probability weighting, the probability that the good outcome obtains (p) 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). Unlike previous research that examined strategy choices of wildfire managers under moderate outcome probabilities,[5] the range of probabilities was selected to investigate risk preferences in a more realistic fire management setting involving high-consequence/low-probability outcomes.

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 $2 \times 2 \times 2 \times 6$ full-factorial design, resulting in 48 unique choice sets. The choice sets were blocked into six blocks of eight choice sets, with potential respondents randomly assigned to one of the six blocks.

3.1. An Information Framing Experiment

This study uses a simple information framing experiment to examine decisions when information about the risks to aviation personnel is presented in different ways. The use of aviation resources accounts for the largest share of fatalities that occur on wildfires, and significant variation exists in the use of aviation among wildfires.[28] The framing

Table I. Attribute Levels Used in the Experimental Design

Attribute	Safe Strategy		Risky Strategy[a]		
	Good	Bad	Good	Bad–Low	Bad–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 million	$14 million
Suppression cost	$300,000	$500,000	$25,000	$2 million	$12.5 million

[a]Each attribute has two potential bad outcomes under the risky strategy. Bad outcomes to the attributes, and the probability the bad outcome would result, were varied systematically among the choice sets using an experimental design.

experiment tests whether changing how risk information is presented to managers—in particular, providing information to prime respondents for affective processing—changes respondents' willingness to expose aviation personnel to the risk of fatalities.

In the control frame of the experiment, half of the surveyed sample received a version of the survey where the aviation exposure attribute was described in terms of aviation-personnel-hours. The treatment frame received a version of the survey with aviation exposure described in terms of the expected number of fatalities resulting from aviation use based on historical fatality rates. Given the focus on safety at the USFS, we expect that highlighting potential fatalities will prime affective processing (rather than analytical processing) among respondents and increase the salience of the aviation risk attribute. Affective processing is necessary to some degree for rational thought and good decision making.[26] When feelings for outcomes are unfavorable (as is likely for personnel fatalities), affective processing may prompt respondents to consider choices to be higher risk and lower benefit,[22] and the increased salience may induce risk aversion toward the aviation risk attribute.[29] Thus, we hypothesize that encouraging affective processing will result in choices that reduce expected fatalities (i.e., result in safer outcomes with respect to aviation personnel).

Forest Service statistics indicate that over the past 10 years, the agency has experienced an average of 4.801 fatalities for every 100,000 flight hours.[30] This average historical fatality rate was used to calculate expected frequencies of fatalities on fires requiring the given levels of aviation exposure. Aviation exposure attribute levels provided to the control group and the corresponding treatment group levels are given in Table II. Both the control and treatment groups were presented with the 10-year average USFS aviation fatality rate in the fire management lottery experiment instructions and attribute description; thus, the control group was presented with information that allowed respondents to calculate the corresponding fatality rate if desired. Example choice sets for the control and treatment groups are provided in Fig. 1.

Table II. Aviation Exposure Attribute Levels for the Control and Treatment Frames

Control	Treatment
10 hours	0.5 deaths in 1,000 fires
50 hours	2.4 deaths in 1,000 fires
75 hours	3.6 deaths in 1,000 fires
300 hours	14 deaths in 1,000 fires
1,200 hours	58 deaths in 1,000 fires

3.2. Survey Administration

The primary population of interest for the experiment is employees with decision-making authority on wildfire incidents. Potential survey respondents were identified using Forest Service public distribution lists of agency administrators and wildfire managers, including fire management officers (FMOs), assistant fire management officers (AFMOs), and command and general staff of incident management teams. Command and general staff of incident management teams sometimes include managers employed by Department of Interior (DOI) agencies in addition to Forest Service employees; however, approximately 95% of the final sample consists of Forest Service employees.

Initial email invitations were sent on April 3, 2012, to a total of 1,934 USFS and DOI employees. The invitation was accompanied by a letter of support from Tom Harbour, USFS Director of Fire and Aviation Management, emphasizing the importance of completing the survey. Invitations included a link to a website where managers could complete

(a) Control frame

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

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

(b) Treatment frame

Strategy A		
90.0% 900 of 1000 wildfires	Aviation Exposure	2.4 deaths in 1000 fires
	Private property damage	$600,000
	Suppression cost	$300,000
10.0% 100 of 1000 wildfires	Aviation Exposure	3.6 deaths in 1000 fires
	Private property damage	$1.25 million
	Suppression cost	$500.000

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

Fig. 1. Strategy choice examples: control (top panel) and treatment (bottom panel) frames.

the web-based questionnaire. In the three weeks following the initial contact, up to three reminder emails were sent to respondents who had not yet started the survey or only partially completed the survey. A total of 1,197 managers provided responses, and of these 1,073 managers completed the fire management lottery experiment portion of the survey. This latter number implies a response rate of 55.5%. Twelve days after the final reminder, a brief follow-up questionnaire was sent to those in the sample frame who had not responded and who had partially completed the survey to investigate their reasons for not completing the survey and potential nonresponse bias.

The final sample used for analysis includes 1,027 respondents after dropping observations with missing data, and a total of 8,156 choice observations (each respondent saw eight lotteries). Characteristics of the sample are given in Table III.

4. EMPIRICAL SPECIFICATIONS

The strategy utility decision model described in Equation (3) can be applied in an empirical setting by taking a probabilistic approach to observed decisions and specifying a distribution for the unobserved random component of choices, ϵ. The likelihood that a respondent chooses the "safe" strategy over the "risky" strategy is expressed as:

$$\Pr[Y = Safe] = \Pr[V_S + \epsilon > V_R + \epsilon], \tag{5}$$

where $V_m = \pi(p_G)v(\mathbf{x}_{mG}|\beta) + (1 - \pi(p_G))v(\mathbf{x}_{mB}|\beta)$ is the utility of the $m = Safe$ or $m = Risky$ strategies, and G and B index the "good" and "bad" outcomes that are possible under each strategy. If a type I extreme value distribution is assumed for ϵ (see Train,[18] Chapter 3), then the likelihood that the "safe" strategy is chosen in a given

Table III. Summary of Sample Individual Characteristics by Treatment Assignment

Characteristic	Var. Name	Control Group	Treatment Group
# of respondents		516	511
		Mean (std. dev.)	
Age	AGE	48.4 (9.33)	49.0 (8.7)
		% of sample[a]	
Position			
Agency Admin.	AA	32.6	35.2
Fire Manager, fuels and fire	MGR_fuel	8.9	11.1
Fire Manager, suppression	MGR_supp	30.3	25.9
Other	POS_oth	28.2	27.5
Experience in fire management			
0–4 years	EXP0_4	7.2	8.0
5–9 years	EXP5_9	13.4	9.0
10–14 years	EXP10_14	15.9	16.6
15–19 years	EXP15_19	16.1	12.9
20–29 years	EXP20_29	30.6	34.1
30+ years	EXP30	16.7	19.4
Education			
HS diploma or less	ED_hs	3.9	3.1
Some coll. or assoc. degree	ED_coll	28.1	26.6
Bachelor's degree	ED_bach	49.6	51.1
Graduate or prof. degree	ED_grad	18.4	19.2
Gender			
Male	MALE	74.5	74.7
Female	FEMALE	25.5	25.3
Agency of employment			
USFS	USFS	96.3	94.1
DOI	DOI	3.1	4.9
GS (pay scale) level			
5–6	GS5_6	4.3	2.9
7–8	GS7_8	13.0	12.2
9–10	GS9_10	13.2	11.2
11–12	GS11_12	34.2	32.8
13–15	GS13_15	33.6	40.0
With respect to managing fires, I am risk averse			
Strongly disagree	RA_sdis	7.6	6.1
Somewhat disagree	RA_dis	36.6	35.6
Neutral	RA_neut	19.2	20.7
Somewhat agree	RA_agr	23.6	27.8
Strongly agree	RA_stag	10.7	8.6
Don't know	RA_dk	2.3	1.2

[a]Percentages may not sum to 100 due to rounding.

choice occasion can be expressed as the familiar conditional logit expression:

$$L(Y = Safe) = \frac{e^{V_S}}{e^{V_S} + e^{V_R}}. \tag{6}$$

In an ELM framework, maximum likelihood can be used to estimate attribute preference parameters (βs) for aviation exposure, property damage, and suppression costs that maximize the joint likelihood of observing the sample choice pattern. Such a model would allow for conclusions about the tradeoffs that managers are willing to make over outcome attributes when making strategy choices, but would assume risk neutrality and linear probability weighting in decisions. For the models described below that allow for probability weighting and nonneutral risk preferences, estimation is conducted using Stata12's "ml" suite of maximum likelihood estimation commands.

4.1. Choice Model with Probability Weighting and Risk Aversion

To test the hypotheses described in Section 2, the empirical form of the strategy utility function is altered to accommodate nonlinear probability weighting and nonneutral risk preferences. A variety of functional forms are available; Stott[31] identifies seven parametric probability weighting functions (PWFs) and seven parametric value functions, and others are also possible. Although several different combinations of weighting and value functions have been used in the literature, a growing set of studies has attempted to estimate risk parameters for risky choices involving multiple outcome attributes (recent examples include Hensher *et al.*,[32] van Houtvan *et al.*,[33] Sun *et al.*,[34] and Wibbenmeyer *et al.*[5]).

This study follows the example of Hensher *et al.*[32] and investigates two versions of the PWF, and a constant relative risk aversion (CRRA) form of the value function. The PWFs include the single-parameter forms presented by Prelec equation (3.1)[35] and Tversky and Kahneman[15] (T&K):[8]

$$\text{Prelec:} \quad \pi(p) = exp{-}(-\ln p)^{\gamma}, \tag{7}$$

$$\text{T\&K}: \quad \pi(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}. \tag{8}$$

For both forms, probability weighting approaches a linear (unweighted) form as $\gamma \to 1$, which is the null hypothesis that is consistent with ELM. As $\gamma \to 0$, the weighting function approximates a step function, where all probabilities are perceived as either zero or one.

The CRRA value function is a variant of the power function used in several contexts to allow for risk-averse preferences over outcomes. With the assumption that attributes enter the utility function linearly and are additively separable, the CRRA strategy utility function becomes:

$$\begin{aligned} V_m = {} & \pi(p_G)\left(\frac{1}{1-\alpha}\right) \\ & \times \left(\beta_{AE} AE_{mG}^{1-\alpha} + \beta_D D_{mG}^{1-\alpha} + \beta_C C_{mG}^{1-\alpha}\right) \\ & + (1-\pi(p_G))\left(\frac{1}{1-\alpha}\right) \\ & \times \left(\beta_{AE} AE_{mB}^{1-\alpha} + \beta_D D_{mB}^{1-\alpha} + \beta_C C_{mB}^{1-\alpha}\right), \end{aligned} \tag{9}$$

[8]Other weighting functions were considered, including an alternative single-parameter form[35] (Equation 3.6) and two-parameter form[36] (Equation 3). Alternative forms tended to result in some combination of a poorer fit for the data, unrealistic parameter estimates, or convergence problems in the likelihood maximization routine. The Prelec and T&K forms both consistently performed reasonably well under a variety of specifications.

where α is the risk preference parameter to be estimated, $\pi(p)$ is either the Prelec or T&K PWF, and AE, D, and C are the aviation exposure, property damage, and suppression cost attributes, respectively. The null hypothesis is that managers are risk neutral, which is defined by $\alpha = 0$. Risk-averse preferences are characterized by $0 < \alpha < 1$, and risk-seeking preferences by $\alpha < 0$.

4.2. Incorporating Heterogeneity

The basic choice models described above implicitly assume that the target population is homogenous in its attribute preferences and responses to risk. However, the functional forms are flexible enough to incorporate manager heterogeneity in a variety of ways. Uncovering how risk preferences vary in the population may be helpful for identifying factors related to decisions that are consistent with agency policy and public preferences, and can aid in providing targeted risk management training. Of particular interest is whether human capital factors (e.g., education, experience, and training) are related to risk preferences.

Heterogeneity of attribute preferences, risk aversion, or probability weighting can be examined in several ways. The most straightforward method is to incorporate classical heterogeneity to condition parameters based on a linear combination of observable individual characteristics. Booij *et al.*[37] use this approach and find that demographic characteristics are related to risk preference parameters. They find greater loss aversion among women and lesser loss aversion among those with more education and greater incomes; older individuals also exhibit slightly more severe probability weighting, although the estimated effect is small. In its simplest form, classical heterogeneity can detect differences in preferences between discrete subpopulations. For example, Fehr-Duda *et al.*[38] find more severe probability weighting among women when making choices over simple gambles.

A shortcoming of the classical approach is that it requires strong assumptions about the nature of heterogeneous preferences, including a determination of observable characteristics thought to influence preferences. Alternatives to the classical approach include latent class models (LCMs), mixture models, and random parameters models. The primary benefit of these types of models is that they allow for insights about how risk preferences vary in the population based on both observable and unobservable characteristics. In a risk context, latent class and mixture models have been used to identify subpopulations that make decisions under discrete risk preference models.[34,39] Random parameters models (e.g., Hensher *et al.*[32]) place fewer restrictions on how preferences are distributed in the population, yet can accommodate observable characteristics that may influence where in the distribution a given individual may fall.

This study investigates how risk preferences vary in the target population using a classical heterogeneity extension to the basic choice models and an LCM. In the former case, individual characteristics are interacted with the risk aversion parameter (α) and the probability weighting parameter (γ) to form a deterministic model of how each parameter varies by selected observable characteristics. An LCM is developed following the approach described in Sun *et al.*[34] and Greene and Hensher.[40] Three versions of a two-class model are estimated, one where class membership is completely determined by unobservables (which corresponds to a finite mixture model), and two where class membership is conditioned on answers to either a risk attitude survey question or reported education.[9]

The LCM proceeds by specifying separate choice probability functions (i.e., Equation (6)) for each class, with the number of classes determined *a priori*. The choice functions can have varying forms in each class, depending on the hypotheses about how unobserved heterogeneity affects choices. For example, Conte *et al.*[39] restrict one class to an expected utility model, and a second class to a rank-dependent utility model with probability weighting. In this study, the underlying choice model is the same with the strategy utility function specified using Equation (9), but with the risk parameters (α and γ) allowed to take unique values for each class. The attribute preference parameters (β) are restricted to be invariant between classes.

In addition to the choice probabilities, the LCM also requires a class-membership probability function. The probability that individual i is a member of class q is expressed as:

$$H_{iq} = \frac{e^{\mathbf{Z}_i' \Theta_q}}{\sum_q e^{\mathbf{Z}_i' \Theta_q}} \quad q = 1, \ldots, Q \quad \Theta_1 = \mathbf{0}. \quad (10)$$

[9]A three-class model without observables was estimated, and resulted in modest improvements in fit over the analogous two-class models. However, three-class models that included observable characteristics to condition class membership exhibited varying degrees of difficulty with convergence during maximization.

When no observables are used to condition the class membership probabilities, the Θ_q parameters describe the mixing distribution, i.e., the probability that a respondent selected at random is a member of each class (when $Q = 2$, as it is in the results described below, Θ_2 describes the probability of being a member of class 2). When individual characteristics $\mathbf{Z}_i$ are included, Θ_q describes how observables are related to the likelihood of membership in each class.

5. RESULTS

Table IV lists attribute and risk preference parameter estimates for the basic choice models. Estimates are presented for both of the PWF forms, and separately for the "control" and "treatment" groups of the information framing experiment. Specifications for both PWFs perform reasonably well and tend to yield similar conclusions about the parameters. A likelihood ratio test was conducted to compare a pooled sample of all respondents regardless of framing group to an unrestricted model that allows for separate parameters for each framing group. For all specifications, the test confirms that separate models are warranted for each framing group.[10]

Results indicate that managers are, broadly speaking, risk averse in their choice of strategies. Across all specifications, the α parameter is estimated between 0.75 and 0.78 and is significantly different from both zero and one with a high level of confidence. Further, framing of the aviation exposure attribute does not appear to influence risk-averse choice behavior.

The probability weighting parameter (γ) indicates that respondents in the control frame—who saw aviation exposure described in terms of personnel-hours rather than fatality rates—appear to respond to probabilities roughly consistent with ELM. For both PWFs, the control group estimate of γ is not statistically distinguishable from one. Thus, for the control group, the hypothesis of linear probability weighting cannot be rejected.

Respondents in the treatment frame exhibit a greater degree of probability weighting. Estimates of

[10]Differences between the control and treatment group were tested using a pooled model with treatment dummy variable interactions for each parameter. The treatment dummy variable for γ was significant at the 95% level, and a likelihood ratio test confirmed that the treatment dummy variables are jointly significantly different from zero, indicating that the treatment and control models should be estimated separately.

Table IV. Choice Model Parameter Estimates by Probability Weighting Functional Form and Treatment Group, No Individual Characteristics

PWF Form:	Prelec PWF (Equation (7))		T&K PWF (Equation (8))	
Attribute	Control	Treatment	Control	Treatment
AvExp	−2.14**	−4.10***	−2.32**	−3.53*
	(0.964)	(1.49)	(0.993)	(1.82)
Dmg	−1.02***	−0.479***	−1.04***	−0.463***
	(0.228)	(0.135)	(0.228)	(0.135)
Cost	−0.407***	0.007	−0.416***	−0.009
	(0.107)	(0.091)	(0.108)	(0.091)
α	0.776***	0.755***	0.764***	0.782***
	(0.065)	(0.072)	(0.062)	(0.098)
γ	0.895***	0.622***	0.913***	0.675***
	(0.086)	(0.067)	(0.070)	(.067)
Choice obs. (N)	4,097	4,059	4,097	4,059
# respond.	516	511	516	511
$ln(L)$	−2,532	−2,585	−2,532	−2,585
AIC	5,075	5,179	5,075	5,179
BIC	5,107	5,211	5,107	5,211

Standard errors, in parentheses, are adjusted for respondent-level clusters. *, **, and *** indicate significance at the 90%, 95%, and 99% levels, respectively.

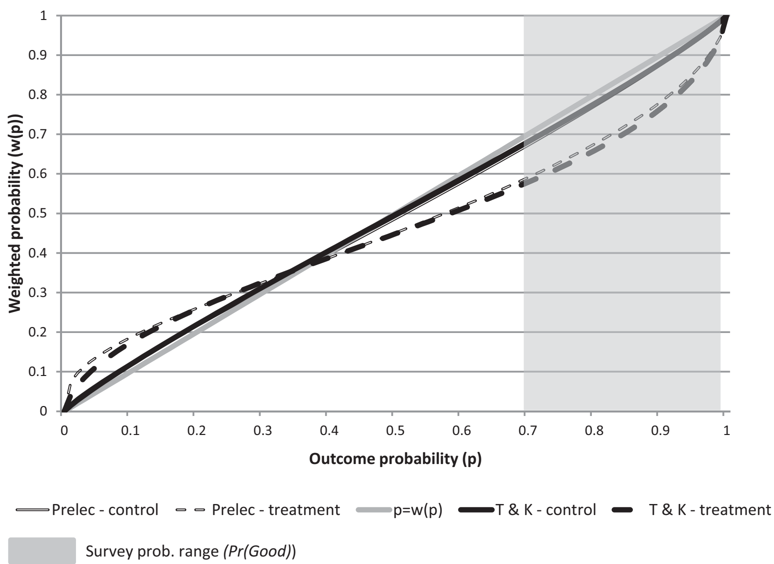

Fig. 2. PWF estimates by PWF form and frame.

γ of 0.622 and 0.675 for the Prelec and T&K PWFs, respectively, are significantly different from one and significantly different from probability weighting estimates in the control frame. The estimates for the treatment group are consistent with an "inverted-S"-shape function where low probabilities are overweighted and high probabilities are underweighted. Fig. 2 displays the estimated PWF functions extrapolated over the entire probability spectrum. For this application, where p_G ranges from 0.7 to 0.995, results suggest that managers are discounting the relatively high probability that a good outcome will result (or, inflating the relatively low probability that a bad outcome will result) when risk to aviation personnel is framed using fatality rates. A consequence of this behavior is that managers avoid opportunities to obtain the best possible results (in the risky–good outcome) because the low probability of a bad outcome is inflated relative to linear weighting.

The focus of this study is on the parameters that describe responses to risk, but attribute preferences are of interest as well. Estimates of the attribute preference parameters are, as expected, generally negative, indicating that increased potential loss of

Table V. Average Change in Property Damage and Suppression Costs Necessary to Compensate for an Increase in the Probability of an Aviation Fatality of 0.1%

PWF Form:	Prelec PWF	T&K PWF
Control frame		
ΔDmg (mil. $)	0.192	0.190
ΔCost (mil. $)	0.431	0.426
Treatment frame		
ΔDmg (mil. $)	0.702	0.751
ΔCost (mil. $)	*na*	*na*

The cost attribute parameters in the treatment frame are not significantly different from zero.

each of the attributes is considered to negatively affect utility, and are significantly different from zero. However, the treatment group makes different tradeoffs over the attributes as compared with the control group. In the treatment group, greater preference is shown for avoiding aviation exposure, and reduced preference for avoiding potential damage to property and increases in suppression costs. In fact, the parameter for suppression costs becomes statistically insignificant for the treatment group, indicating that respondents did not consider the magnitude of this attribute when making choices. This finding is consistent with Calkin *et al*,[6] where managers in their professional capacity appeared to have a slight preference for strategies with higher suppression costs.

Table V illustrates the tradeoffs between attributes implied by respondent choices in the control and treatment groups. The values represent the average amount in dollars that either property damage or suppression costs would need to change to compensate respondents for an increase in the risk of an aviation fatality of 0.1%. In the control frame, the marginal increase in fatality rates would require an average decrease of about $191,000 of expected property damage and $430,000 in suppression costs to hold utility constant. In the treatment frame, managers are less willing to make tradeoffs to accept increases in the aviation personnel fatality rate. When respondents saw aviation fatality rates, an average decrease in expected property damage of more than $700,000 would be required to compensate for the 0.1% increase in the fatality rate, and respondents are essentially unwilling to trade suppression costs for changes in the fatality rate (because the coefficient for suppression costs is not statistically different from zero).

Table VI. Average Expected Attribute Outcomes Based on Predicted Choices and Expected Loss Minimization Choices, Prelec PWF Only

Control Frame	Predicted Choices	ELM Choices	Difference
AvExp (deaths per 1,000 fires)	2.94	2.63	0.312
Dmg (mil. $)	1.03	0.789	0.240
ce6ptCost (mil. $)	0.473	0.354	0.119
Treatment frame	**Predicted Choices**	**ELM Choices**	**Difference**
AvExp (deaths per 1,000 fires)	2.75	2.97	−0.220
Dmg (mil. $)		0.904	0.097
Cost (mil. $)	0.470	0.461	0.009

Note: Expected attribute outcomes and differences are similar when calculated using parameter estimates from the Tversky and Kahneman form of the probability weighting function.

5.1. Expected Attribute Outcomes

To examine the consequences of probability weighting, risk aversion, and framing on the expected outcomes of each attribute, predicted choices based on the estimated models are compared to choices that would occur if respondents exhibited ELM (i.e., linear probability weighting and risk neutrality; see Equation (4)). Choice probabilities (for the risky and safe options) are calculated for each respondent choice occasion, and expected outcomes are calculated for each attribute based on the likelihood that the good or bad outcome is realized. Maintaining the assumption of independence between risk preferences and attribute preferences, the attribute preference parameters are the same for expected attribute outcomes under observed and ELM choices.

Average expected attribute outcomes under observed choices and ELM choices are presented in Table VI. In the control frame, expected attribute outcomes for all three attributes are higher for observed choices compared with ELM choices. Risk aversion has the effect of making the risky strategy less appealing, which pushes respondents to choose the strategy that has higher expected attribute outcomes but involves less risk. Estimated probability weighting places additional decision weight on the low-probability bad outcomes, although the PWF parameters are not significantly different from linear probability weights for the control sample.

The treatment frame suggests that highlighting the risks to aviation personnel can have an impact on choices and expected attribute outcomes. Under observed choices, expected aviation personnel fatalities is actually lower than it would be with ELM choices. Respondents chose strategies that avoided expected aviation fatalities, although at the cost of higher property damage and suppression costs (as compared with ELM choices). The magnitude of the effect suggests eliminating probability weighting and risk aversion would add an expected 2.2 aviation fatalities per 10,000 fires.

5.2. Models with Heterogeneity

Allowing for heterogeneous responses to risk provides additional insight into manager risk preferences. Table VII presents the estimates for the classical heterogeneity regression, where α and γ are conditioned on either risk attitudes (in the case of α) or individual characteristics (in the case of γ). The degree of risk aversion appears to be largely homogeneous within the population based on responses to a risk attitude question.[11] The population-wide parameter estimate is still close to one, indicating significant risk aversion, and risk attitudes specifically referencing risk aversion in a fire management context have only limited explanatory power. There is evidence that some respondents in the treatment frame are less risk averse at a significance level greater than 95%: respondents who neither agreed nor disagreed with the statement that they are risk averse in a fire management context had slightly less risk-averse preferences compared to the rest of the sample.

More variation is evident for probability weighting. Probability weighting appears to be more severe than the homogenous model would suggest, but individual characteristics such as years of experience in fire management and education attainment are associated with less severe probability weighting. Further, the effect of education is larger in the treatment frame. For a manager with more than 20 years of experience and a bachelor's or graduate degree, probability weighting is nearly eliminated compared to a manager with fewer years of experience and with a high school diploma or less. Results are consistent with the idea that managers with more education and experience may be ignoring the additional affective content provided in the treatment frame and focusing on the analytical component of information.

The LCMs (Table VIII) take a different approach to describing how risk preferences vary among managers. Instead of estimating specific risk

Table VII. Estimates of Risk Parameters that Vary by Individual Characteristics, by Probability Weighting Functional Form, and Treatment Group

PWF Form:	Prelec PWF (Equation (7))		T&K PWF (Equation (8))	
Attribute	Control	Treatment	Control	Treatment
α	0.928***	0.897***	0.811***	0.952***
	(0.077)	(0.081)	(0.248)	(0.129)
RA_dis	−0.003	−0.035	−0.005	−0.036
	(ins0.038)	(0.035)	(0.039)	(0.035)
RA_neut	−0.046	−0.121**	−0.054	−0.123**
	(0.044)	(0.049)	(0.048)	(0.049)
RA_agr	−0.079*	−0.064*	−0.082*	0.064*
	(0.044)	(0.037)	(0.046)	(0.036)
RA_stag	−0.129*	−0.040	−0.140*	−0.042
	(0.067)	(0.049)	(0.073)	(0.049)
RA_dk	−0.288	0.026	−0.337	0.025
	(0.177)	(0.078)	(0.270)	(0.078)
γ	0.183*	−0.067	0.482***	0.237***
	(0.109)	(0.100)	(0.110)	(0.070)
AA	0.122	−0.004	0.175	−0.006
	(0.078)	(0.080)	(0.525)	(0.049)
EXP9	−0.019	0.239*	−0.023	0.155*
	(0.090)	(0.127)	(0.083)	(0.083)
EXP14	0.234**	0.228**	0.244	0.0142*
	(0.106)	(0.105)	(0.357)	(0.073)
EXP19	0.132	0.081	0.166	0.051
	(0.115)	(0.092)	(0.409)	(0.057)
EXP29	0.146	0.193**	0.152	0.121**
	(0.093)	(0.082)	(0.298)	(0.055)
EXP30	0.196*	0.202**	0.144	0.124**
	(0.102)	(0.078)	(0.101)	(0.052)
ED_COLL	0.215**	0.357***	0.157	0.220***
	(0.096)	(0.092)	(0.110)	(0.060)
ED_BACH	0.386***	0.498***	0.346	0.307***
	(0.107)	(0.103)	(0.505)	(0.070)
ED_GRAD	0.366***	0.532***	0.271*	0.327***
	(0.113)	(.122)	(0.156)	0.081
Choice obs. (N)	4,097	4,059	4,097	4,059
# respond.	516	511	516	511
$ln(L)$	−2,450	−2,513	−2,453	−2,515
AIC	4,938	5,064	4,945	5,068
BIC	5,058	5,184	5,065	5,188

Standard errors, in parentheses, are adjusted for respondent-level clusters. *, **, and *** indicate significance at the 90%, 95%, and 99% levels, respectively. Attribute parameters suppressed for brevity (available upon request).

[11] A variety of alternative specifications using other risk attitude questions and individual characteristics were used to condition α. The presented specification represents the best fit among alternatives, and was the only specification that exhibited evidence of variation within the population.

Table VIII. Latent Class Model Estimates by Frame for Two Classes, Prelec PWF Only

	Control Frame			Treatment Frame		
Attribute	(1)	(2)	(3)	(4)	(5)	(6)
AvExp	−0.899***	−1.01***	−0.878***	−2.23***	−2.16***	−2.22***
	(0.237)	(0.282)	(0.227)	(0.535)	(0.514)	(0.532)
Dmg	−1.02***	−0.997***	−1.01***	−0.878***	−0.889***	−0.875***
	(0.168)	(0.167)	(0.167)	(0.159)	(0.161)	(0.159)
Cost	−0.589***	−0.583***	−0.590***	−0.194*	−0.192*	−0.192*
	(0.095)	(0.096)	(0.095)	(0.106)	(0.107)	(0.106)
Θ_2	0.331**	0.637	−1.08**	0.489***	1.04**	−2.06**
	(0.159)	(0.396)	(0.549)	(0.130)	(0.462)	(0.896)
RA_dis		0.425			−0.390	
		(0.454)			(0.486)	
RA_neut		−0.245			−1.22**	
		(0.447)			(0.503)	
RA_agr		−0.379			−0.741	
		(0.447)			(0.491)	
RA_stag		−0.804*			−0.302	
		(0.481)			(0.577)	
RA_dk		−1.75**			−0.141	
		(0.880)			(1.10)	
ED_COLL			0.906			2.26**
			(0.590)			(0.911)
ED_BACH			1.76***			2.68***
			(0.573)			(0.902)
ED_GRAD			1.65***			2.72***
			(0.610)			(0.920)
γ_1	0.170***	0.169***	0.165***	0.139***	0.138***	0.137***
	(0.021)	(0.023)	(0.021)	(0.020)	(0.020)	(0.021)
γ_2	0.719***	0.730***	0.703***	0.676***	0.670***	0.672***
	(0.070)	(0.072)	(0.068)	(0.063)	(0.062)	(0.063)
α	1.01***	0.987***	1.02***	0.951***	0.957***	0.951***
	(0.045)	(0.047)	(0.045)	(0.047)	(0.047)	(0.047)
Choice obs. (N)	4,097			4,059		
# respond.	516			511		
$ln(L)$	−2,251	−2,242	−2,241	−2,188	−2,181	−2,179
AIC	4,517	4,508	4,501	4,390	4,387	4,377
BIC	4,566	4,592	4,572	4,439	4,471	4,447

Standard errors in parentheses. *, **, and *** indicate significance at the 90%, 95%, and 99% levels, respectively.

preference parameters for groups of managers with different characteristics, the LCMs identify patterns of response with respect to risk within the sample and estimate a likelihood of each individual making choices consistent with each pattern. The estimated LCMs with two classes indicate that a portion of the sample exhibits severe probability weighting (where $\gamma < 0.18$) and the remaining portion of the sample exhibits moderate probability weighting (γ about 0.7). This distinction appears to hold in both the framing control and treatment samples, although the estimated PWF parameters are slightly lower in the treatment group.

The LCMs are agnostic as to why differences exist in the sample, but can be used to describe the likelihood of individuals belonging to each class. Two specifications are estimated to explore factors that are related to the likelihood of class membership (described by the Θ_2 parameter). Self-reported risk aversion in a fire management context may partially explain class membership in the control group. Those who strongly agree that they are risk averse or do not know are less likely to be members of class 2 (which is the class with less-severe probability weighting). In the treatment group, only those who responded with "neutral" (i.e., neither agree nor disagree that they are risk averse) were less likely to be members of class 2.

Education attainment has a clearer relationship with class membership. In both the control and treatment frames, greater educational attainment is associated with a greater likelihood of membership in class 2. This finding is consistent with the classical heterogeneity model; in this case, managers with higher educational attainment are more likely to be among the group of managers who exhibit less-severe probability weighting.

A limitation of the heterogeneity findings is that the models presented here cannot establish that obtaining greater education (or experience) causes managers to make decisions that exhibit different responses to risk. As public agencies involved in wildfire management seek to improve risk management, an important question to answer will be whether investments in human capital (e.g., through training, education, or experience) can result in changes in decisions that improve wildfire outcomes. Such questions are left for future research.

6. DISCUSSION

The results of the empirical analysis broadly support the notion that decisions made by wildfire managers in an experimental setting are subject to common risk biases. Managers' choices exhibit risk aversion, meaning that on average managers are more likely to choose a "safe" option over a more risky one even when the expected losses of the risky option are lower, similar to results from financial lotteries (e.g., Holt and Laury[27]). Risk aversion appears to be relatively uniform across the respondent sample and invariant to information framing, although additional empirical investigation is necessary to rule out heterogeneity based on additional characteristics or risk attitudes. Managers also tend to overweight low probabilities and underweight high probabilities. Probability weighting appears to vary more than risk aversion in the sample, and becomes more severe when information on one of the outcome attributes is framed to prime affective processing in decision making.

The results confirm the existence of common risk-decision-making biases, such as risk aversion and probability weighting, which have been identified in a wide variety of settings and associated with wildfire management in past research.[3–5] A unique contribution of the present study is the consideration of the magnitude of effect of manager risk preferences on expected wildfire outcomes, at least in a stylized experimental setting.

Tradeoffs between attributes that managers make when choosing strategies change when we attempt to encourage affective processing. When risk to aviation personnel is presented as expected fatalities instead of a usage rate, managers have a greater preference to avoid the risk of aviation-related fatalities at the expense of greater property damage and suppression costs. The reduced willingness among managers to make tradeoffs with aviation exposure suggests that priming for affective processing can have an impact on the relative importance of different outcomes from wildfires. This result is consistent with the finding that affective processing encourages higher risk and lower benefit judgments when feelings for outcomes are more negative,[22] as well as theories of choice where the salience of payoffs affects preferences and risk responses.[29] In the present case, focusing on potential fatalities may cause managers to place less weight on the benefits of deploying aviation personnel and the other negative outcomes associated with wildfires.

Priming affective processing also appears to exacerbate overweighting of low probabilities and underweighting of high probabilities. This may suggest that the priming results in affective processing overwhelming analytical processing when choosing among strategies, consistent with experiments that control for affective content in risk decisions.[41] The results in the present study are consistent with the role of affect as a determinant of risk preferences and S-shaped responses to probabilities,[25,26] although we do not explicitly examine the role of affect richness independent of priming for affective processing.

Priming for affective processing appears to alter the expected attribute outcomes relative to choices made when affective processing is not primed. When potential aviation fatalities are highlighted, observed risk preferences result in choices that reduce expected fatalities and increase property damage and suppression costs as compared with choices based on an ELM strategy. To summarize, the choices managers make when primed for affective processing make aviation personnel safer, but at the expense of greater losses to other attributes. Slovic *et al.*[9] suggest that affective processing may alleviate the neglect of statistical information (resulting in greater weight placed on aviation personnel safety relative to other attributes), but may also encourage insensitivity to probability (resulting in the overweighting of low-probability outcomes). However, this study does not attempt to disentangle the relative contribution of these effects to the expected outcomes for aviation fatalities, property damage, and suppression costs.

Finally, an analysis of how risk preferences vary among managers reveals evidence that individual characteristics are associated with differences in probability weighting. In particular, managers with more experience and education tend to exhibit less-severe probability weighting and make choices more consistent with ELM strategies. However, further research aimed at examining heterogeneity in this context is needed to establish the robustness of this result.

One implication of the results is that risk preferences are an important determinant of how managers balance the benefits and costs of wildfire management efforts (e.g., avoided damages vs. the potential for fatalities). The apparent risk aversion and probability weighting estimated from the sample data represent significant departures from strategy choices that would be consistent with the minimization of expected losses from wildfires. In general, the pattern of estimated risk preferences implies that managers are missing opportunities to take "good bets" on strategies that can result in outcomes with low personnel exposure to risk, property damage, and suppression costs. This behavior is due in part to a preference to avoid risk, and a tendency to place less weight on high-probability good outcomes than is consistent with ELM. However, in the framing treatment, ELM would result in greater expected fatalities.

A second implication is that the content of information presented to managers matters for making strategy decisions. Managers increasingly have a wealth of information available about the fires that they manage. In this study, altering how one attribute was described to managers had significant effects on attribute preferences and responses to risk. This result may serve as both a caution for the design of decision support tools and an opportunity to engage managers in discussions about the factors that influence their decisions. The way information is shared and represented during a wildfire has been associated with differing levels of effectiveness among management teams;[(42)] the results of the present study may provide a behavioral link between responses to risk and decisions that affect outcomes of a fire, although much remains to be learned. For example, it is not yet known to what degree the decisions of wildfire managers are consistent with models of rapid decision making, such as the recognition-primed decision model.[(43)]

Several caveats to the analysis limit the broad applicability of results, and suggest future avenues of research. In particular, the results are obtained with hypothetical choice data gathered using a one-time survey instrument. Although the survey and experiment were designed to accurately elicit risk attitudes and preferences from managers, it is not possible to say that the results are representative of how real wildfires have been managed in the past or of all the factors that can affect strategy decisions. For example, responses to risk may be influenced by manager career prospects and sociopolitical considerations,[(44)] which are not accounted for here. Partly, this is by design; the highly stylized wildfire scenario and strategy choices were developed to be a reasonable but simplified exercise in wildfire decision making. Further, the survey experiment does not fully capture the dynamic and uncertain environment that wildfire managers operate in. A more complete understanding of risk attitudes of public managers could benefit from incorporating temporal and spatial elements, such as observing a series of strategy choices where outcomes and available strategies depend on past decisions.

ACKNOWLEDGMENTS

The authors thank participants of the Harvard Center for Risk Analysis's "Risk, Perception, and Response" conference (March 2014) and the University of Montana Department of Economics seminar series (March 2014), and two anonymous reviewers for their helpful comments on earlier drafts. Mr. Wibbenmeyer received a small honorarium from the Harvard Center for Risk Analysis for preparing the article. The findings and conclusions of this article are those of the authors and do not necessarily represent the views of the U.S. Department of Agriculture.

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