Risk preferences, inefficiencies, and opportunities in wildfire management

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Abstract

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 in the spring of 2012. Respondents were presented with a multi-attribute 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 non-linear probability weighting, which can result in choices that do not minimize expected losses from wildfires. Information framing tends to result in greater probability weighting and greater value placed on risks to firefighters.

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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 ten years, the U.S. Forest Service has spent about $10.2 billion (in 2012 dollars) on wildfire suppression. Institutional incentives and socio-political factors are likely important determinants of decisions and costs (Calkin et al., 2011; Donovan et al., 2011), 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 sub-optimal outcomes for individuals (Maguire and Albright, 2005; Wilson et al., 2011).

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 sub-optimal outcomes from a public perspective. Building on previous research on wildfire manager decisions (Wibbenmeyer et al., 2013; Calkin et al., 2013), a survey-based experiment is used to elicit choices among strategies by Federal wildfire managers in a hypothetical wildfire scenario. A random utility model is adapted to allow for non-linear 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 non-expected utility model of wildfire management decisions

Wildfire management is a complex decision environment where managers must make strategic decisions that balance multiple objectives in a risky world.[1] 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.

The null hypothesis in this study is that managers make decisions that avoid common risk biases, are coolly analytical and ignore affective information processing described in Epstein (1994) and Slovic et al. (2004), and manage risks to minimize the total expected losses.[2] 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 (Mees et al., 1994; Yoder, 2004; Haight and Fried, 2007; Konoshima et al., 2008). 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. The manager utility function may represent personal or professional preferences, and may or may not correspond to the public's preferences over

[1] 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.

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

potential wildfire outcomes.[3] No assumption is made about how managers form their preferences, only that their preferences can be represented by a well-behaved utility function. The utility of a given outcome j is defined as:

$$v(j) = v(\mathbf{x}_j|\beta), \tag{1}$$

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 make decisions of which strategies to pursue knowing that multiple potential outcomes may occur with varying probabilities. A strategy utility function is adapted from cumulative prospect theory (Tversky and Kahneman, 1992), 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:

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

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 j^{th} outcome.

Preferences over strategies are related to choices by incorporating risk within a random utility model (RUM) of choice over multi-attribute goods. The basic random utility model is the basis for a wide range of empirical choice studies (see McFadden, 1973; Louviere et al., 2000; Train, 2009, 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

[3] 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 (Calkin et al., 2013).

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,

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

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.[4]

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

2.1 Effects of framing on manager choices

It is well-established that decisions involving risk are governed by several factors other than responses to outcome probabilities and levels. This is also likely true for the population of wildfire managers in particular (Maguire and Albright, 2005; Wilson et al.,

[4] The linear-in-parameters utility function also corresponds to the functional form of utility functions used for empirical analysis of discrete choice (see Train, 2009, 41). An underlying assumption when using the linear form is that utility is additively separable in the attributes.

2011). Wildfire managers have access to a wide and increasingly detailed array of information about the incidents they manage, including qualitative, quantitative, and geo-spatial information (Noonan-Wright et al., 2011). Decision support systems are also becoming a key tool for implementing a risk management decision framework for wildfire managers (Calkin et al., 2011). 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 (Tversky and Kahneman, 1981), and affect decision-makers' degree of risk aversion in lottery choices (Lévy-Garboua et al., 2012). Framing effects may arise because presenting information in different ways changes 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 (1981)) or because of changes in how people perceive the salience and importance (e.g., value) of potential outcomes. If people are able to accurately perceive the content of information independently of the method of presentation, 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 (Apicello, 2011). An explicit goal of the agency's prioritization of safety is to change how decisions are made to yield different–and safer–outcomes (Hubbard, 2012). Examining how safety information affects decisions on wildfire incidents can indicate the degree to which the method that the agency uses to describe safety consequences is an impediment or potential tool for improving outcomes.

In this case, framing is investigated in terms of information that may have different affective content. Affective content can influence the emotional connection decision makers have for potential outcomes (Rottenstreich and Hsee, 2001; Slovic and Peters, 2006). If this exists for fire managers, it is expected that an informational frame designed with greater affective content for an outcome attribute would change the relative value managers place on attributes (i.e., the relative magnitudes in the β vector) and the willingness to accept risk of losses to that attribute (i.e., degree of probability weighting and risk aversion).

3 A multi-attribute lottery experiment

To test whether wildfire managers exhibit decision making consistent with expected loss minimization, 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, 2002) to estimate risk aversion and probability weighting parameters in an experimental sample. 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.

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 damage, 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 1. 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 non-linearly to changes in outcome probabilities when making wildfire strategy decisions (i.e., that respondents weight outcome probabilities). 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 (Wibbenmeyer et al., 2013), 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 are presented in different ways. The framing experiment tests whether changing how risk information is presented to managers–in particular, changing the affective content–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. 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 (USDA Forest Service, 2010). This average historical fatality rate was used to calculate expected frequencies of fatalities on fires requiring the given levels of aviation exposure. The treatment frame received a version of the survey with aviation exposure described in terms of these expected frequencies. Aviation exposure attribute levels provided to the control group and the corresponding treatment group levels are given in table 2. 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 choice set are provided in Figure 1.

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 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 web site where managers could complete 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 non-response 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 3.

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, 2009, ch. 3), then the likelihood that the "safe" strategy is chosen in a given choice occasion can be expressed as the familiar conditional logit expression:

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

In an ELM framework, maximum likelihood can be used to select attribute preference parameters (β's) 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 non-neutral 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 non-linear probability weighting and non-neutral risk preferences. A variety of functional forms are available; Stott (2006) identifies seven parametric probability weighting functions 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 have attempted to estimate risk parameters for risky choices involving multiple outcome attributes (recent examples include Hensher et al. (2011), Van Houtven et al. (2011), Sun et al. (2012) and Wibbenmeyer et al. (2013)).

This study follows the example in Hensher et al. (2011) and investigates two versions of the probability weighting function, and a constant relative risk aversion (CRRA) form of the value function. The probability weighting functions include the single-parameter forms presented in (Prelec, 1998, eqn. 3.1) and Tversky and Kahneman (1992) (T&K)[5]:

$$\text{Prelec (1998):} \quad \pi(p) = exp{-}(-\ln p)^{\gamma}, \tag{7}$$

$$\text{Tversky and Kahneman (1992):} \quad \pi(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}. \tag{8}$$

For both forms, probability weighting approaches a linear (unweighted) form as $\gamma \to 1$, which is the null hypothesis that is consistent with expected loss minimization. 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 is 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,

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

where α is the risk preference parameter to be estimated, $\pi(p)$ is either the Prelec or T&K probability weighting function, and AE, D, and C are the aviation exposure, property damage, and suppression cost attributes, respectively. The null hypothesis is that

[5] Other weighting functions were considered, including an alternative single-parameter form (Prelec, 1998, eqn. 3.6) and two-parameter form (Gonzalez and Wu, 1999, eqn. 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.

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 their 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. (2010) use this approach and find that age, education, and income appear to be related to risk preference parameters. In its simplest form, classical heterogeneity can detect differences in preferences between discrete sub-populations (e.g., by gender (Fehr-Duda et al., 2006)).

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, 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 sub-populations that make decisions under discrete risk preference models (Conte et al., 2011; Sun et al., 2012).

Random parameters models (e.g., Hensher et al., 2011) place fewer restrictions on how preferences are distributed in the population, yet can accommodate observable characteristics that may influence where in the distribution an 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 a latent class model (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. A latent class model is developed following the approach described in Sun et al. (2012) and Greene and Hensher (2003). 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 conditioned on either answers to a risk attitude survey question or reported education.[6]

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. (2011) 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.[7] 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

[6] 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.

[7] Preliminary regressions found that the risk-aversion parameter, α, did not vary between classes.

as,

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

When no observables are used to condition the class membership probabilities, the $\mathbf{\Theta}_q$ 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, $\mathbf{\Theta}_q$ describes how observables are related to the likelihood of membership in each class.

5 Results

Table 4 lists attribute and risk preference parameter estimates for the basic choice models. Estimates are presented for both of the probability weighting function (PWF) forms, and separately for the "control" and "treatment" groups of the information framing experiment. Specifications for both probability weighting functions 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.

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 expected loss minimization. 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 γ of 0.622 and 0.675 for the Prelec and T&K PWFs, respectively, are significantly different from one. The estimates for the treatment group are consistent with an "inverted-S" shape function where low probabilities are over-weighted and high probabilities are under-weighted. Figure 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 they see aviation personnel 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 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 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. (2013) where managers in their professional capacity appeared to have a slight preference for strategies with higher suppression costs.

5.1 Models with heterogeneity

Allowing for hetergeneous responses to risk provides additional insight into manager risk preferences. Table 5 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.[8] 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. Only in the treatment frame is there evidence that some respondents are less risk averse at a significance level greater than 95%: respondents who neither agreed or 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 latent class models (LCM) (table 6) take a different approach to describing how risk preferences vary among managers. Instead of estimating specific risk preference

[8] 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

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 don't 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 that 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 the decisions wildfire managers make over management strategies 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. 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 exhibit non-linear probability weighting, over-weighting low probabilities and under-weighting 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 highlight negative consequences.

Manager preferences over outcome attributes respond to information framing. When exposure of aviation personnel to risk is presented as a fatality rate instead of a usage rate, manager preferences exhibit greater avoidance of additional aviation exposure at the expense of a reduced focus on property damage and suppression costs. These altered attribute preferences suggest that in an experimental setting the affective content of risk information can have an impact on the relative importance of different outcomes from wildfires.

One implication of the results is that risk preferences are an important determinant of the efficiency of risk management efforts for wildfire incidents. 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 expected loss minimization.

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. While this result may serve as a caution for the design of decision support tools, it can also represent an opportunity to engage managers in discussions about the factors that influence their decisions. An interesting extension to this study would be to conduct the framing experiment with a training module that would allow managers to explicitly process risk information in a more analytical (as opposed to affective) way.

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. 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.

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Table 1: Attribute levels used in the experimental design.

	Safe strategy		Risky strategy[a]		
Attribute	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 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. Bad outcomes to the attributes, and the probability the bad outcome would result, were varied systematically among the choice sets using an experimental design.

Table 2: Aviation exposure attribute levels for the control and treatment frames.

Control	Treatment
10 hours	0.5 deaths in 1000 fires
50 hours	2.4 deaths in 1000 fires
75 hours	3.6 deaths in 1000 fires
300 hours	14 deaths in 1000 fires
1200 hours	58 deaths in 1000 fires

Table 3: 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 Mgr., fuels and fire	MGR_fuel	8.9	11.1
Fire Mgr., suppression	MGR_supp	30.3	25.9
Other	POS_oth	28.2	27.5
Experience in fire mgmt.			
0–4 yrs.	EXP0_4	7.2	8.0
5–9 yrs.	EXP5_9	13.4	9.0
10–14 yrs.	EXP10_14	15.9	16.6
15–19 yrs.	EXP15_19	16.1	12.9
20–29 yrs.	EXP20_29	30.6	34.1
30+ yrs.	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
Grad. 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.

Table 4: Choice model parameter estimates by probability weighting functional form and treatment group, no individual characteristics

PWF form:	Prelec (1998) (Eqn. 7)		Tversky and Kahneman (1992) (Eqn. 8)	
Attribute	Control	Treatment	Control	Treatment
AvExp	-2.14**	-4.10***	-2.32**	-3.53*
	(.964)	(1.49)	(.993)	(1.82)
Dmg	-1.02***	-.479***	-1.04***	-.463***
	(.228)	(.135)	(.228)	(.135)
Cost	-.407***	.007	-.416***	-.009
	(.107)	(.091)	(.108)	(.091)
α	.776***	.755***	.764***	.782***
	(.065)	(.072)	(.062)	(.098)
γ	.895***	.622***	.913***	.675***
	(.086)	(.067)	(.070)	(.067)
Choice obs. (N)	4,097	4,059	4,097	4,059
# respond.	516	511	516	511
$ln(L)$	-2532	-2585	-2532	-2585
AIC	5075	5179	5075	5179
BIC	5107	5211	5107	5211

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

Table 5: Estimates of risk parameters that vary by individual characteristics, by probability weighting functional form and treatment group

PWF form:	Prelec (1998) (Eqn. 7)		Tversky and Kahneman (1992) (Eqn. 8)	
Attribute	Control	Treatment	Control	Treatment
α	.928***	.897***	.811***	.952***
	(.077)	(.081)	(.248)	(.129)
RA_dis	-.003	-.035	-.005	-.036
	(.038)	(.035)	(.039)	(.035)
RA_neut	-.046	-.121**	-.054	-.123**
	(.044)	(.049)	(.048)	(.049)
RA_agr	-.079*	-.064*	-.082*	.064*
	(.044)	(.037)	(.046)	(.036)
RA_stag	-.129*	-.040	-.140*	-.042
	(.067)	(.049)	(.073)	(.049)
RA_dk	-.288	.026	-.337	.025
	(.177)	(.078)	(.270)	(.078)
γ	.183*	-.067	.482***	.237***
	(.109)	(.100)	(.110)	(.070)
AA	.122	-.004	.175	-.006
	(.078)	(.080)	(.525)	(.049)
EXP9	-.019	.239*	-.023	.155*
	(.090)	(.127)	(.083)	(.083)
EXP14	.234**	.228**	.244	.142*
	(.106)	(.105)	(.357)	(.073)
EXP19	.132	.081	.166	.051
	(.115)	(.092)	(.409)	(.057)
EXP29	.146	.193**	.152	.121**
	(.093)	(.082)	(.298)	(.055)
EXP30	.196*	.202**	.144	.124**
	(.102)	(.078)	(.101)	(.052)
ED_COLL	.215**	.357***	.157	.220***
	(.096)	(.092)	(.110)	(.060)
ED_BACH	.386***	.498***	.346	.307***
	(.107)	(.103)	(.505)	(.070)
ED_GRAD	.366***	.532***	.271*	.327***
	(.113)	(.122)	(.156)	.081
Choice obs. (N)	4,097	4,059	4,097	4,059
# respond.	516	511	516	511
$ln(L)$	-2450	-2513	-2453	-2515
AIC	4938	5064	4945	5068
BIC	5058	5184	5065	5188

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).

Table 6: Latent class model estimates by frame for two classes, Prelec PWF only

	Control frame			Treatment frame		
Attribute	(1)	(2)	(3)	(4)	(5)	(6)
AvExp	-.899***	-1.01***	-.878***	-2.23***	-2.16***	-2.22***
	(.237)	(.282)	(.227)	(.535)	(.514)	(.532)
Dmg	-1.02***	-.997***	-1.01***	-.878***	-.889***	-.875***
	(.168)	(.167)	(.167)	(.159)	(.161)	(.159)
Cost	-.589***	-.583***	-.590***	-.194*	-.192*	-.192*
	(.095)	(.096)	(.095)	(.106)	(.107)	(.106)
Θ_2	.331**	.637	-1.08**	.489***	1.04**	-2.06**
	(.159)	(.396)	(.549)	(.130)	(.462)	(.896)
RA_dis		.425			-.390	
		(.454)			(.486)	
RA_neut		-.245			-1.22**	
		(.447)			(.503)	
RA_agr		-.379			-.741	
		(.447)			(.491)	
RA_stag		-.804*			-.302	
		(.481)			(.577)	
RA_dk		-1.75**			-.141	
		(.880)			(1.10)	
ED_COLL			.906			2.26**
			(.590)			(.911)
ED_BACH			1.76***			2.68***
			(.573)			(.902)
ED_GRAD			1.65***			2.72***
			(.610)			(.920)
γ_1	.170***	.169***	.165***	.139***	.138***	.137***
	(.021)	(.023)	(.021)	(.020)	(.020)	(.021)
γ_2	.719***	.730***	.703***	.676***	.670***	.672***
	(.070)	(.072)	(.068)	(.063)	(.062)	(.063)
α	1.01***	.987***	1.02***	.951***	.957***	.951***
	(.045)	(.047)	(.045)	(.047)	(.047)	(.047)
Choice obs. (N)	4,097			4,059		
# respond.	516			511		
$ln(L)$	-2251	-2242	-2241	-2188	-2181	-2179
AIC	4517	4508	4501	4390	4387	4377
BIC	4566	4592	4572	4439	4471	4447

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

Figure 1: Strategy choice occasion examples, control and treatment frames

(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

Figure 2: Probability weighting function estimates, by PWF form and frame