Behavioral Responses towards Risk Mitigation: An Experiment with Wild Fire Risks

by

J. Greg George, Glenn W. Harrison, E. Elisabet Rutström and Shabori Sen†

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ABSTRACT. What are the behavioral effects of allowing for risk mitigation in situations where the probabilities are unknown to the agent? Virtually all naturally occurring environments of risk management involve subjective probabilities, and allow decision makers to mitigate risk as well as make choices over risky alternatives. To examine this environment we design a laboratory experiment in which incomplete information about probabilities is generated in a naturalistic way from the perspective of decision makers, but where the experimenter has complete information. Specifically, we use virtual simulations of property that is at risk of destruction from simulated wild fires. We find that subjective beliefs are significantly affected by the presence of self protection opportunities, leading to over investment in mitigation. These findings have direct implications for the normative evaluation of risk management policies when risk perception is subjective.

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† School of Business and the Center for Economic Analysis, Macon State College (George); Department of Risk Management & Insurance, Robinson College of Business and Center for the Economic Analysis of Risk, Georgia State University (Harrison); Dean's Behavioral Economics Lab, Robinson College of Business and Department of Economics, Andrew Young School of Policy Studies, Georgia State University (Rutstrom); Department of Economics, College of Business Administration, University of Central Florida (Sen). E-mail: greg.george@maconstate.edu, gharrison@gsu.edu, erutstrom@gmail.com and shaboris@gmail.com. We thank the U.S. National Science Foundation for research support under grants NSF/HSD 0527675 and NSF/SES 0616746.

Most interesting choices in risky environments allow individuals to undertake self-protection actions that alter the risk that they face. In the business world this is one component of what is called risk management. Using the formal metaphor of economics, individuals choose the probabilities that apply to each outcome in a risky prospect, rather than just choosing between risky prospects with given probabilities. Consider the case of the risk that a wild fire, caused by a lightning strike, burns down your house. The likelihood of a lightning strike is exogenous, thus a homeowner cannot affect this event. However, this likelihood does not translate directly into an exogenous probability of damage to the house, since the homeowner can take various actions to mitigate that risk, such as removing dead wood and debris in the surrounding landscape.

Importantly, in almost all cases of voluntary risk management the risk is not precisely known. In such circumstances, an important determinant of the willingness to undertake risk mitigation is the subjectively perceived probability of damage. Experiments using virtual reality provide an ideal study environment in which the probability can be known to the researcher but unknown to the decision maker. It is also an environment that incorporates many natural cues about the risk and is a unique aspect of this study. We observe how this perception is influenced by the way that the experimenter elicits the subjective probabilities. Following Ehrlich and Becker (1972), EB, we distinguish between risk mitigation actions that affect the probability of damage, referred to as self-protection, and actions that affect the monetary consequences of damage if it occurs, referred to as self-insurance. These actions form the analytical core of the discipline of "risk management," and apply to individuals, enterprises, and public agencies.[1]

[1] In a review of the evolution of insurance economics since 1973, Loubergé (2000; p. 7) notes that Ehrlich and Becker (1972) "… were the first to propose a rigorous analysis of risk prevention. They coined the terms self-protection and self-insurance to designate the two mechanisms and studied their relationship to 'market insurance.' For this reason, this paper may be seen as the first theoretical paper on risk management."

We compare two methods of eliciting the subjective beliefs: one is a betting mechanism over given but unknown probabilities, in our case a betting instrument, and one where the subject has the option to mitigate the risk through self protection, i.e. change the unknown probabilities by expressing a willingness to pay. In the risk mitigation treatment we give subjects the costly option of managing the forest using prescribed burns, thereby decreasing, but not eliminating, the amount of wild fire fuel and the risk of high cost fires. This choice is discrete: either implement a certain level of prescribed burn or not. This is a natural choice structure when using prescribed burn as the fire management tool since there is not a choice of how much of the fuel to burn, but only the choice to burn it all or not. The subject owns a virtual house in the virtual forest, and we model salient incentives by giving the house a monetary value that will be paid out to the subject at the end of the experiment if the house has not burned. We ask the question: "Are beliefs elicited over exogenously given risk the same as beliefs inferred from self protection?" If not, then one cannot use beliefs elicited over exogenously given risk to predict self protecion choices.

Controlling for risk attitudes, we find that our subjects drastically overestimate loss probabilities. However, in the treatments with exogenous risk they underestimate the *reduction* in the loss probability that results from the prescribed burn. On the other hand, when placing the same subjects in situations with voluntary self-protection opportunities, they in fact over- rather than underestimate the reduction in the loss probability resulting from the prescribed burn. Thus, if we want to predict how much would be voluntarily invested in risk mitigation based on the elicited subjective probabilities, the manner in which we elicit these probabilities matter in important ways. Thus, deviations from optimality under self-insurance, where probabilities are exogenous, would not be the same as deviations under self-protection. The finding that subjects overestimate the risk reduction that results from their mitigating investment resembles experimental findings of over confidence in market entry experiments.[3] In these experiments subjects overestimate their ability to make profits post entry, and entry decisions are therefore suboptimal.

We agree with Shogren and Crocker (1994, p. 4) that "…recognition of the frequently endogenous nature of risk raises questions about the assessment-management bifurcation now common in scientific policy discussions about environmental risks to human health and property." Self-protection makes loss probabilities endogenous, so that policies based on actuarial probabilities derived from natural sciences can lead to suboptimal recommendations. We add to their insights the observation that agents do not perfectly estimate the loss probabilities, and that these estimates may be influenced by psychological values that depend on the extent to which individuals perceive their control over the risk. This possibility was hinted at by Shogren and Crocker (1994, p. 1) when referring to how a psychological inability to cope with risk may cause decision makers to misperceive it systematically.

Shogren (1990) observes choices under both self-protection and self-insurance in an experiment where subjects face risky options with known probabilities. The risky options are designed so as to completely eliminate the possibility of a loss. The self-protection and the self-insurance schemes differ in both expected value and variance. The valuations observed, while supporting the claim that the two schemes are not seen as symmetric by the agents, are therefore not designed to answer our question. Shogren (1990) asks whether valuations of risk mitigation options when probabilities are known are higher for the self-protection option than the self-insurance option when the former has both a larger expected gain and a larger reduction in risk. Shogren does not address our question of whether elicitation methods resembling self-insurance and self-protection affect the inferred probabilities, when the latter are unknown to the subject. We further contribute to the understanding of risk

[3] See Camerer and Cavallo (1999)

mitigation decisions by estimating structural models of choice that allow us to separate preference effects from perception effects on valuations.

In a related experiment Bruner (2009) observes how choices between a certain amount and a risky lottery change as probabilities are varied and as outcomes are varied. Using a design where subjects choose between a certain and a risky option, and where probabilities are known he reports no significant differences in the estimated constant relative risk aversion (CRRA) coefficient across these formats.

In the next section we briefly review the theory of self-protection and self-insurance of EB. We then describe our experimental design, our econometric strategy, and then give a detailed account of our estimation results.

I. Theory

Suppose there are two states of nature: for example, your house burns or it does not. We review here the expected utility theory of risk mitigation from EB. Let the probability of damage be p. Then the expected utility of an individual is given by:

$$\text{EU}= [1-p]U(x)+pU(x-l)$$

where x is initial wealth, l is the loss experienced, and no mitigation is possible.

EB distinguished between two forms of mitigation – self-insurance and self-protection. *Self-insurance* investment consists of expenditures made to reduce the value of the loss caused by the occurrence of the house burning. Define the loss function as $L = L(l, c)$ where c is self-insurance investment; $L'(c)$ is assumed to be negatively sloped, implying that loss decreases as self-insurance increases. The agent's problem now is to choose c to maximize:

$$\text{EU} = (1-p)U(x-c)+pU(x-L(l,c)-c)$$

For self-insurance investment to be positive $-L'(c)>1$ must hold.

Self-protection is investment made to reduce the probability of incurring any damages when the bad outcome occurs. Let $P = P(p, d)$ be the effective risk function that takes into account the ability of the individual to change the risk faced, and where p is the exogenous risk of damage occurring, d is the expenditure on self-protection, and $P'(d) < 0$. In the absence of market or self-insurance the agent's problem is then to choose self-protection investment d to maximize:

$$\text{EU} = [1 - P(p,d)]U(x-d) + P(p,d)U(x-l-d)$$

where l is the dollar damage caused. Self-protection is the only available mitigation alternative in our experiments.

In this model the probability of damage, conditional on the bad outcome occurring, is itself a function of the investment made by the individual to reduce risk. Allowing for self-protection makes risk endogenous, since here the risk P is affected by the mitigation activity undertaken by the individual. Note that an individual has the same utility *function*, whether or not risk can be mitigated, although the *level* of utility may of course differ in the two cases. This implies that if the utility function, the exogenous underlying probability, and the risk mitigation function are known, it is possible to predict the optimal level of mitigation.

Further, recognizing that the perceived probability of the risk may not be equal to the actual, objective probability since the latter is not known to the agent, the theory is amended with a function that maps p to the experiences and information that agents use to form their beliefs. Thus p could be modeled as

$$\pi = f(p, e, I)$$

where π is the perceived, subjective probability, a function of the actual objective probability p, experiences e, and information I. In our virtual reality simulations we allow subjects to gain experience so that, for any given objective probability p, the perceived probability π may change. In addition, experiences and information may not affect all subjective probabilities equally, and may not affect them the same way under different choice conditions. We would then have the risk mitigation function $\Pi = \Pi\ (\pi, d\ )$.

Our main hypothesis is that $\Pi_d > P_d$ the perceived damage probability under self-protection is greater than it is in the absence of self-protection.

II. Experimental Design

The experimental design is built on a naturalistic presentation of the risk of damages, where Virtual Reality (VR) simulations are used to mimic natural risk, but where no precise, numeric information of probabilities is given to subjects. This methodology provides a methodologically important intermediate environment between field experiments and lab experiments. The natural cues of field experiments are mimicked through simulated naturalistic cues in the VR environment, while still allowing the rigorous controls of a lab experiment. Our VR simulation is of wild fires in the Ashley National Forest in Utah, where the subject is the owner of a log cabin that gives him a monetary payout if it does not burn. The design includes a number of tasks that allow identification of the factors that theoretically influence decisions, including risk attitudes and probability perceptions. These tasks include two betting tasks, three willingness to pay (WTP) tasks, a standard lottery task in the gain domain, and a standard lottery task in the loss domain.

Each of the 7 tasks involves a series of binary choices.[4] Every subject participates in all tasks, and one task is randomly selected at the end of the experiment to determine the subjects' earnings, following common experimental practice.[5] This has the advantage of

[4] Subjects were given 11 tasks, but only 7 are analyzed here. The additional 4 tasks were given after these 7.

[5] A simple procedure is used to ensure that the random nature of this process is credible, using the following instructions: "The box in front of you has 11 envelopes and 11 cards numbered 1 through 11. Please put one card into each envelope and close the envelopes. I will now shuffle these envelopes. The envelopes have now been carefully shuffled and I ask that you pick one of them. The number on the card in the envelope you selected determines which task you will be paid for. But you will not know which one until the end of the

avoiding any "wealth or portfolio effect" that may arise if subjects are paid for multiple decisions made at the same time.

The betting tasks and the WTP tasks use VR simulations of wild fires, and are used to elicit subjective probabilities with and without self-protection. These tasks constitute the core of the experiment, where subjects do not know the exact probabilities over events. Instead each outcome is generated by running simulations with a set of parameters that determine the intensity, speed and direction of spread of a wild fire. These parameters are stochastic with known, discrete distributions. The effects that various combinations of these factors have on the wild fire are not known to the subjects, but they are given some limited exposure to that relationship before making their choices. This mimics the limited information conditions that are common in field decision situations.

A considerable amount of time in the experiment is spent on the instructions for the VR tasks, including an extensive explanation of the betting mechanism. We control for order effects by varying whether subjects experience the VR betting task first, followed by the VR WTP task, or *vice versa*. Following the VR tasks, subjects are also given a series of lottery tasks with known probabilities, intended to elicit risk attitudes.

The next section describes in detail the VR tasks used to elicit subjective beliefs. We explain both the betting mechanism and the WTP task. We then explain 6 lottery tasks with known probabilities. These vary in terms of the use of gain and loss frames, and in terms of the choices being made over monetary outcomes or over probabilities.

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experiment when you will be allowed to open the envelope." All experiments were conducted with one subject at a time.

The Virtual Reality Simulations

Subjects are told that the VR simulations are based on the Ashley National Forest in Utah, and that they have a virtual property in this area in the form of a log cabin. The path of the simulated fire spread is generated using FARSITE, a fire behavior simulation model developed by Finney (1998) and widely used by fire management professionals. The rendering software that performs the visual simulation of the forest and the fire is from Fiore, Harrison, Hughes and Rutström (2009), FHHR. The simulated area is subject to wild fire, and in the WTP task they must make a decision whether to pay for a prescribed burn or not, which would reduce the risk that their property would burn. The prescribed burn option is discrete: either the entire forest is prescribed burn and all excess fuel removed or not. There is no option to do partial burns. There are no VR simulations of the prescribed burn itself. The prescribed burn only matters as the cause for the high or low fuel loads that generate the high *vs.* low risk scenarios.

Subjects receive 3 pieces of information about the risk to their property. First, they are told that the background uncertainties are generated by (a) temperature and humidity, (b) fuel moisture, (c) wind speed, (d) duration of the fire, and (e) the location of the ignition point. They are also told that these uncertainties are binary for all but the last, which is ternary; hence there are 48 background scenarios. They are also told what the specific values are for these conditions (e.g., low wind speed is 1 mph, and high wind speed is 5 mph). Thus subjects could use this information, their own sense of how these factors play into wild fire severity, and their experiences and inferences from the VR experience, explained below, to form some probability judgments about the risk to their property. The objective is to provide information in a natural manner, akin to what would be experienced in the actual policy-relevant setting, even if that information does not directly "tell" the subject the probabilities.

Second, the subject is shown some histograms displaying the distribution of acreage in Ashley National Forest that is burnt across the 48 scenarios. Figure 1 shows the histograms presented to subjects. The vertical axis is deliberately scaled in terms of natural frequencies defined over the 48 possible outcomes, and the scaling of the axes of the two histograms is identical to aid comparability. The qualitative effect of the enhanced prescribed burn policy is clear: to reduce the risk of severe wild fires. Of course, the information here is about the risk of the entire area burning, and not the risk of their personal property burning, and that is pointed out in the instructions.

Third, subjects are allowed to experience several of these scenarios in a VR environment that renders the landscape and fire as naturally as possible. Figure 2 illustrates the type of graphical rendering provided, although static images such as these do not do justice to the VR "presence" that was provided. Some initial training in navigating in the environment is provided, which for this software is essentially the same as in any so-called "first person shooter" video game.[6] The mouse is used to change perspective and certain keys are designated for forward, backward, and sideward movements, as well as up and down. The subject is then presented with the 4 practice scenarios and is then free to explore the environment, the path of the fire, and the fate of their property during each of these. Apart from the ability to move across space, subjects also have the option of moving back or forth in time within each fire scenario.[7]

With this approach, subjects are able to form their own beliefs about the probability of damage. Contrary to decisions involving actual lottery tickets in most laboratory experiments, this risk management environment has outcomes and probability distributions

[6] For student subjects this interface is second nature.
[7] This points to another feature of the VR environment in settings where current action, or inaction, can lead to latent effects well into the future. The VR simulation interface can be used by subjects to "fast forward" and better comprehend those effects.

that are not completely known to the agent. We therefore expect the choices to be affected by individual differences not just in risk perceptions but also in risk preferences. We are particularly interested in the perception of risk that subjects form in this VR experiment, since this drives decisions on risk mitigation. Hence the instructions are designed to convey information about this risk as accurately as possible without explicitly giving numeric probabilities.

The instructions start with a brief introduction about the threats of wild fires and of prescribed burning as a fire management tool that can reduce the frequency and severity of fires. The idea of VR computer simulations is introduced, followed by instructions that explain the first experimental task, which is either the betting task or the WTP choice task. We vary the order of these 2 tasks across subjects. This is followed by a discussion of how the 5 background factors in the simulation affect the risk of damages to their property. We use dice to select background factors for each simulation, so that the likelihood of these selections is known, even though the effects they have on the risk to property are not. Subjects are made familiar with the idea that fires and fire damages are stochastic, and can be described through frequency distributions. They are shown the frequency distributions of the forest acreage burnt under all possible combinations of background factors as generated by the simulation program. They are not, however, shown frequency distributions of damage to their own property. The subjects then experience 4 dynamic VR simulations of specific wild fires, 2 for each of the cases with and without previous prescribed burns, rendered from the information supplied by FARSITE simulations that vary weather and fuel conditions. We selected these simulations to represent the most benign and the most intensive combination of factors for fire spread, and the subjects are told this. They are allowed to experience these simulations in any way they like. They may move around the landscape however they want, and they may move back and forth in time freely.

After having had the opportunity to form beliefs about the likelihood of the property burning in a fire, subjects are presented with the choice tasks. When all choice tasks are completed, one is selected randomly for payment. If the selected task involves a VR simulation, then as part of determining earnings a final simulation is run, using randomly selected background factors. These random selections are performed using dice. Whether or not the property burns in this final simulation impacts the earnings in the task.

We first describe the betting and WTP tasks where payments depend on outcomes of the VR simulations. Thereafter we describe the tasks that do not use VR simulations, but instead use objective probabilities implemented using dice.

The Betting Tasks

The objective of the betting task is to directly recover the subject's belief that event A will occur instead of event B. Event A is when the property burns and event B is when it does not, so the two events are mutually exclusive. Assume that the subject is risk neutral and has no stake in whether A or B occurs other than the bets being made on the event. There are 9 bookies, each willing to take a bet at stated odds. Table 1 shows odds for the two events in the form that they are naturally stated in the field: what is the amount that the subject would get for a $5 bet if the indicated event occurred? Each row in Table 1 corresponds to a different bookie with different odds.

In our design the subject is simply asked to decide how they want to bet with each of the 9 bookies, understanding that only one of these bookies may be the one selected for payment at the end of the experiment. Their "switch point," over the 9 bookies, is then used to infer their subjective belief. The basic experimental design and estimation strategy are borrowed from FHHR and Andersen, Fountain, Harrison and Rutström (2010).[8] Consider a subject that has a personal belief that A will occur with probability 0.75, and assume that the subject *has* to place a bet with each bookie, knowing that only one of these bookies will actually be played out. The (risk neutral) subject would rationally bet on A for every bookie offering odds that corresponded to a lower probability than 0.75 of A winning, and then switch over to bet on B for every bookie offering odds that corresponded to a higher probability than 0.75 of A winning. These bets are shown in Table 1, and imply gross earnings of \$50 or \$0 with the first bookie, \$25.00 or \$0 with the second bookie, and so on. The expected gross earnings from each bookie can then be calculated using the subjective belief of 0.75 that the subject holds. Hence the expected gross earnings from the first bookie are $(0.75 \times \$50) + (0.25 \times \$0) = \$37.50$, and so on for the other bookies. A risk neutral subject with the subjective probability 0.75 would bet on event A for the first 7 bookies and then switch to event B.

Each subject faces two betting tasks in our experiment. The first task is for the event that the house burns when the fuel load is high (or a prescribed burn is not used); and the second task is for the event that the house burns when fuel level is low (or a prescribed burn is used). Thus, the objective probability in the first task is higher than in the second. The subject is given a fictional \$5 stake to bet with in each of the 2 betting tasks, and a bet has to be placed for each of the 9 bookies. The stakes are fictional in that the subject cannot choose not to bet. Furthermore, the \$5 for one bookie is not transferable to other bookies, and one of the bets will be selected at random to be actually played out.

[8] Familiar scoring rule procedures are formally identical, since each probability report implicitly generates a bookie willing to bet at certain odds. Thus when the subject makes a report in a Quadratic Scoring Rule, for example, the subject is in effect choosing to place a bet on the event occurring with payoffs given by odds that are defined by the scoring rule. By making one report instead of another, the subject is then choosing one bet over another, or equivalently, in our design, one bookie over another.

If a betting task is selected to be played out, then a final simulation would be run to determine the earnings. This simulation would either have a high or a low fuel load, depending on which betting task is selected. All other background factors are randomly selected. In the betting tasks the subjects cannot affect the probabilities that the house will burn. These tasks therefore do not offer self-protection options.

The WTP Tasks

The design of the WTP choice task offers subjects self-protection options. Earnings to subjects depend on an initial endowment of money, the monetary value of their property, and whether or not the property burns. The subjects have the option to use some or all of their initial money endowment to pay for a prescribed burn. Recall that the amount of prescribed burn, or the amount of removed fuel, is given so the choice is either to prescribe burn all of the forest or none. After having viewed the 4 simulations from which they form their subjective beliefs, subjects are shown a list of prices that can be charged for a prescribed burn. Table 2 shows this list for one of the three WTP tasks. In this task the property is worth $8 if it survives the fire, and the initial money endowment is $20. The first row shows the case where self-protection is free: the price of prescribed burn is $0. For each row below that the cost of a prescribed burn increases by $2 until a maximum price of $8 is reached. On each row the subject will choose either Yes, for agreeing to pay the price and have a prescribed burn done, or No, for preferring to keep the money and not having a prescribed burn. Only one row could potentially be selected for payment.

There are three such WTP tasks that differ by how much the house is worth and the level of the initial endowment. In addition to the task with a house valued at $8 and an initial endowment of $20, there is a task where the house is valued at $28 with an initial endowment of $60, and a task where the house is valued at $38 with an initial endowment of

$80. Using these multiple tasks allows us to identify both the probability of the high risk case and the probability of the low risk case. The choice data generated in these 3 tasks can be analyzed as data from a series of pairwise options, but using subjective probabilities since the objective probabilities are not known to subjects. Whether or not one uses the betting task data or the WTP task data to infer probabilities, it is important to control for risk attitudes. We use additional choice tasks that present subjects with risky options with known probabilities to infer risk attitudes.

Choice Tasks with Known Probabilities

We present subjects with several pairwise choice tasks where the probabilities are precisely known and no VR simulation is used. All of these choice tasks use ordered lists of pairs of lotteries, which we call lotteries S or R. The letter S (R) refers to the relatively safer (riskier) of the two lotteries. Table 3 illustrates the basic payoff matrix presented to subjects in the first such task, which we will refer to as the standard lottery task. The first row of Table 3 shows a choice between getting $24 for certain (lottery S) or $1 for certain (lottery R). The second row shows a more interesting choice, where lottery S offers a 90% chance of receiving $24 and a 10% chance of receiving $26. The expected value of this lottery is shown as $24.20, although the EV columns are not presented to subjects. Similarly, lottery R in the second row has prizes $50 and $1, for an expected value of $5.90. Thus the two lotteries have a difference in expected value of $18.30. As one proceeds down Table 3, the expected value of both lotteries increases, but the expected value of lottery R becomes greater relative to the expected value of lottery S.

Each subject chooses S or R for each row, and only one row may later be selected at random for payment. The logic behind this test for risk aversion is that only risk loving subjects would take lottery R in the second row, and only very risk averse subjects would take lottery S in the last row. Arguably, the first row is simply a test that the subject understood the instructions, and has no relevance for risk aversion at all. A risk neutral subject should switch from choosing S to R when the EV of each is about the same, so a risk neutral subject would choose S for the first five rows and R thereafter. In each row the subject is equally likely to get the bigger prize or the smaller prize, which rules out the possibility of self-protection; the only difference is the payoff amount.

The second choice task using known probabilities presents the subjects with the same pairwise lottery choices as in the standard lottery task, but now they are framed as losses instead of gains. For example, instead of winning \$26 the subject now loses \$24 from an initial endowment of \$50, with probabilities applied as before. Accordingly, for an endowment of \$50 our prizes after "reflections" into a loss framing become -\$24, -\$26, -\$0 and -\$49.[9] The basic hypothesis to be tested is that the risk aversion coefficients in the gain and loss frames are identical. This task is illustrated in Table 4.

Our primary interest in restating the standard lottery task in the loss frame is to make it comparable with the framing of other tasks in our experiment. Both the betting tasks and the WTP tasks are stated as losses from initial endowments, mimicking how fires in the naturally occurring field imply losses from some initial property endowment. The lotteries in the gain and loss frame are, however, identical only to the extent that the assumption about the reference point being a \$0 prize in the lottery is valid. As emphasized in Harrison and Rutström (2008; p.95ff.), it is difficult to determine the reference point that the subject actually uses in tasks such as these. It is possible, for instance, that the subject has a reference point of \$50, such that he views all of the net prizes in the loss frame lottery as positive and therefore perceives no losses. The expected values of the lotteries with \$0 and

[9] Holt and Laury (2008) undertook a similar exercise but where subjects earned their initial endowment in earlier experimental tasks, which averaged \$43 and ranged from \$21.68 to \$92.08. They find evidence of risk averse behavior in the gain domain and risk loving behavior in the loss domain.

\$50 reference points are the same. Hence in either case a risk neutral subject chooses lottery S for the first five rows and lottery R for the last five rows.[10]

Allowing for loss aversion, it is possible that subjects make different choices in the lotteries presented in Tables 3 and 4 if they perceive a reference point of \$0. We test whether estimated risk aversion coefficients in the gain and loss domains are identical and whether there is evidence of such a framing effect.

III. Results

We have two kinds of tasks: lottery tasks with known objective probabilities and VR tasks with probabilities unknown to the subject. We can infer risk attitudes from the observations on choices in the lottery tasks. We can then infer subjective probabilities from the observations on choices in the betting and WTP tasks that rely on VR simulations as providing information about risk. The sample consists of 57 subjects recruited from the student population of the University of Central Florida.

Estimating Risk Attitude under Expected Utility Theory (EUT)

We assume that utility is defined by

$$U(x) = \lambda x^{(1-r)}/(1-r)$$

where x is the lottery prize and $r \neq 1$ is a parameter to be estimated. Thus r is the CRRA coefficient, where $r = 0$ corresponds to risk neutrality, $r < 0$ to risk loving, and $r > 0$ to risk aversion. The parameter λ captures a possible reflection effect when the lottery outcome is framed as a loss (and is set equal to one in the gain frame). The variable x in the estimation

[10] Of course, \$0 and \$50 are not the only two possible reference points. If the subject integrates the show up fee of \$5 into his wealth coefficient, then the reference points are \$5 ands \$55 respectively. If he integrates his lifetime income or income outside the current experiment things get more complicated. Inferences about lotteries in the loss domain are very sensitive to assumptions about the reference point.

is then the net payoffs, i.e. the initial endowment minus the loss.[11] All lotteries used in our experiment have two outcomes. If the probability of the worse outcome is *p*, expected utility (EU) is simply the probability weighted utility of each outcome in each lottery *i,*

$$EU_i = (1-p)U(x_g) + pU(x_b)$$

The subscript *g* on the lottery prize *x* indicates the good outcome and the subscript *b* indicates the bad outcomes. The choice depends on the difference in EU between lottery S (safe) and R (risky):

$$\nabla EU = EU_R - EU_S$$

This latent index, based on latent preferences, is then linked to the observed choices using a standard cumulative normal distribution function $\Phi(\nabla EU)$. This "probit" function takes any argument between $\pm\infty$ and transforms it into a number between 0 and 1 using the function shown in Figure 3. Thus we have the probit link function,

prob (choose lottery R) = $\Phi(\nabla EU)$

This function forms the link between the observed binary choices, the latent structure generating the index, and the probability of that index being observed. The conditional log-likelihood function is then

$$\ln L(r; y.X) = \sum_i [(\ln \Phi(\nabla EU) \times I(y_i = 1)) + (\ln(1-\Phi(\nabla EU)) \times I(y_i = -1))]$$

where $I(.)$ is the indicator function and $y_i = 1$ (-1) indicates the choice of the R (S) lottery. The only variable that has to be estimated from this log-likelihood function is *r*.

An important extension of the core model is to allow subjects to make errors in the decision process. The notion of error is one that has already been encountered in the form of the statistical assumption that the probability of choosing a lottery is not 1 when the EU

[11] Allowing more flexible functional forms that model possible income effects, such as the Expo-Power function of Saha (1993), does not affect our findings in any significant manner.

of that lottery exceeds the EU of the other lottery. This is implicitly assumed when one adopts a link function, of the kind shown in Figure 3, to go from the latent index to observed choices. The contextual error specification, suggested by Wilcox (2011), introduces a normalizing term ν for each lottery pair, and a structural "noise parameter" μ to allow for error from the deterministic EU model:

$$\nabla EU = [(EU_R - EU_S)/\nu]/\mu$$

The normalizing term ν is defined as the maximum utility over all prizes in this lottery pair minus the minimum utility over all prizes in this lottery pair, and ensures that the *normalized* EU difference $(EU_R - EU_S)/\nu$ remains in the unit interval. This normalization allows one to define robust measures of "stochastic risk aversion," in parallel to the deterministic concepts from traditional theory. When $\mu = 1$ we return to the original specification without error. As μ increases, the above index falls until, at $\mu = \infty$, it collapses to zero, so that the probability of either choice becomes ½. In other words, as the noise in the data increases, the model has less and less predictive power until at the extreme the prediction collapses to 50:50 or equal likelihood of both choices.

To allow for subject heterogeneity with respect to risk attitudes, the parameter r is modeled as a linear function of observed individual characteristics of the subject. For example, assume that we only had information on the age and sex of the subject, denoted **age** (in years) and **female** (0 for males, and 1 for females). Then we would estimate the coefficients α, β and η in $r = \alpha + \beta \times \text{age} + \eta \times \text{female}$. The covariates we use are all binary. The variable **Age** is given in years over 17; **Female** is a dummy for whether the subject is female or male; **Hispanic** is a dummy for Hispanic heritage; **Business** is whether or not the subject is a business major; **GPAhigh** is for subjects with a self-reported GPA higher than 3.24; **Works** is a dummy for whether or not the subject is employed.

In this design multiple responses are elicited from each subject. This may lead to clustering, or heteroskedasticity. Therefore while estimating the model it is essential to correct for clustering effects. We estimate this model on the data from all the lottery tasks with known probabilities: the standard lottery, the loss frame lottery and the four self-protection frame lotteries. These results are shown in Tables 5a, 5b and 5c.

We find evidence of modest risk aversion, with a CRRA coefficient of 0.33 as shown in Table 5a, consistent with a large body of existing literature reviewed by Harrison and Rutström (2008). None of the demographic variables we include is individually significant in Table 5b. Importantly, we do not find a framing effect of the task being presented in the loss frame, as shown in Table 5c. The coefficient for λ, which would indicate a reflection effect, is 1.12 and not significantly different from 1. Because of this result we can simplify our analysis by not including this parameter in our further analysis.

Jointly Estimating Belief and Risk Attitudes under SEUT

Subjective beliefs about the risk of property damage from fires can be inferred from both the betting tasks or from the WTP tasks. The beauty of using a controlled VR experiment is that, even though probabilities are not known to subjects, they are known to the experimenter. We control for the risk attitude of subjects by jointly estimating risk attitudes and beliefs, using data from all choice tasks for the same subject.

A subject that bets on the house burning (B) in the betting tasks receives the EU given by

$$EU|_{bet\ on\ B} = \pi_B \times U\text{ (payout if B occurs } | \text{ bet on B)}$$
$$+ (1-\pi_B) \times U\text{ (payout if NB occurs } | \text{bet on B)}$$

where NB refers to the event "the house does not burn," and π_B is the subjective probability that B will occur. We use the notation π for the subjective probability to distinguish it from *p*, the objective probability. The example in the second row of Table 1 now is evaluated as

$$EU\,|_{bet\ on\ B} = \pi_B \times (25)^{(1-r)}/(1-r) + (1-\pi_B)\times U(0)^{(1-r)}/(1-r)$$

and

$$EU\,|_{bet\ on\ NB} = \pi_B \times (0)^{(1-r)}/(1-r) + (1-\pi_B)\times (6.25)^{(1-r)}/(1-r)$$

where the event A refers to when the house burns down and event B refers to when it does not. The index function is again

$$\nabla EU = [(EU_{NB} - EU_B)/\nu]/\mu$$

An increase in this index should increase the likelihood of betting on event NB rather than event B. Subjects have 2 betting tasks, one for the forest that has been prescribed burn (the safe case) and one for the forest that has not been prescribed burn (the risky case). Thus the probabilities, π_B, will not be the same for the two betting tasks, so we elicit both π_B^{risky} and π_B^{safe}.

In the WTP tasks π_B^{safe} is the subjective probability of the house burning down when prescribed burning is implemented, and π_B^{risky} is the subjective probability that the house will burn down if no prescribed burning is implemented. More generally,

$$EU_{safe} = \pi_B^{safe} \times U(\text{payout net of cost of prescribed burn if B})$$

$$+ (1-\pi_B^{safe}) \times U(\text{payout net of cost of prescribed burn if NB})$$

and

$$EU_{risky} = \pi_B^{risky} \times U(\text{payout if B})$$

$$+ (1-\pi_B^{risky}) \times U(\text{payout if NB}).$$

The latent index in this problem is the difference in EU from paying for prescribed burning and not paying for prescribed burning:

$$\nabla EU = [(EU_{risky} - EU_{safe})/\nu]/\mu$$

An increase in this index should increase the likelihood of selecting the risky option, i.e. of not paying for prescribed burn. Apart from r, ν and μ, we now need to estimate the two subjective probabilities π^{safe} and π^{risky}. The *joint* maximum likelihood problem is to find the values of all of these parameters that best explain observed choices in the belief elicitation tasks, WTP tasks and lottery tasks.

Detailed maximum likelihood estimates are contained in Table 6. We estimate this model including observations on all 7 tasks. The lottery tasks with known probabilities serve the purpose of identifying risk attitudes, and we confirm that adding data from the betting and WTP tasks does not change the estimated risk attitude appreciably. The pooled estimate of *r* shown in Table 6 is 0.33, and is not affected by adding the VR tasks.

We find evidence that subjects overestimate the loss probabilities both for the safe and the risky case. In Table 6 the constant terms reflect the betting task, and the WTP terms are the equivalent estimates for the WTP task. The constant term for the perceived probability with prescribed burn , π_A^{safe}, is 0.40 instead of the objective value 0.06; and the perceived probability without prescribed burn, π_A^{risky}, is 0.56 instead of the objective value 0.29.

These overestimations lead to higher predicted willingness to invest (WTI) than if based on the objective probabilities, but only in the presence of self protection options. We infer the WTI from the Certainty Equivalents (CE). Using the *objective probabilities* and the estimated risk attitudes we find a CE for the safe case of \$19.48 and a CE for the risky case of \$17.54. These numbers are based on the task where the house is worth \$8, so would be higher for the tasks where the house is worth more. The difference between these CE is the WTI in a prescribed burn, which is \$1.94, with a 95% confidence interval of [\$1.90, \$1.98]. If instead we calculate the CE based on the *subjective probabilities* from the betting tasks, which are much higher, we find an implied WTI of $1.27, with a 95% confidence interval of [$0.99, $1.55]. The overestimation of the safer probability, π_B^{safe}, thus has a stronger influence on the WTI than the overestimation of the riskier probability, π_B^{risky}, such that the implied WTI for prescribed burn is less than one would find based on the objective probabilities. The confidence intervals of the objectively and subjectively calculated WTI do not overlap, so this is a statistically significant shift. The exact dollar values appear small only because these calculations are based on the low house value of $8. For a house value of $28 one would instead find a WTI of $6.87 based on objective probabilities and $4.45 based on subjective probabilities.

When subjects are able to engage in self protection, as in the *WTP tasks* shown by the WTP coefficient in Table 6, we find that the subjective probability for the risky case goes to 1.0, but the subjective probability for the safe case drops to 0.31. The CE when the house is valued at $8 is now $12.00 and $17.53, respectively for the high and low risk case, resulting in a much higher WTI of $5.53 with a 95% confidence interval of [$4.99, $6.08]. Again, this interval does not overlap with the objective interval or the interval without self-protection options, so the shift is statistically significant. When the house is valued at $28 the WTI for mitigation is $19.27. Figure 4 shows the distributions of the subjective probabilities from a model that includes our demographic variables. Not only do we see that the implied WTI is higher with self-protection than without self-protection, we also see that the inferred subjective probabilities are much more dispersed in the former case.

Thus, based on the betting task alone one may be tempted to conclude that voluntary risk mitigation would lead to underinvestment, but once subjects are allowed to self-protect they are in fact overinvesting in mitigation.

IV. Conclusion

Risk attitudes and subjective beliefs are two fundamental determinants of decision making under risk and risk management. Virtually all field settings in which there is risk and uncertainty allow for the ability to mitigate risk through some form of insurance or self-protection. Surprisingly, much more attention has been given to risk settings that do not allow for such measures. Our results provide evidence that behavior is quite different in these two settings. There does not appear to be significant differences in attitudes to risk, but subjective beliefs are shown to vary significantly. Estimating voluntary risk mitigation investments based on subjective probabilities elicited using betting instruments (or standard scoring rules) can lead to dramatic underestimates. Conclusions regarding the optimality of voluntary investment levels, and the implied role for government risk regulation, require that subjective beliefs be elicited under conditions when mitigation options are present. The practical implications of this are important since in many cases it may not be possible to design mitigation options for study purposes short of undertaking the full voluntary investment.

Table 1. Betting Task with Stake of $5

Bet on A and earn if…		*Bet on B* and earn if…		Gross expected value of betting when probability of A is 0.75		
A occurs	B occurs	A occurs	B occurs	A	B	Difference
$50	$0	$0	$5.55	$37.50	$1.39	$36.11
$25	$0	$0	$6.25	$18.75	$1.56	$17.19
$16.65	$0	$0	$7.15	$12.50	$1.79	$10.71
$12.5	$0	$0	$8.35	$9.38	$2.09	$7.29
$10	$0	$0	$10	$7.50	$2.50	$5.00
$8.35	$0	$0	$12.5	$6.26	$3.13	$3.13
$7.15	$0	$0	$16.65	$5.36	$4.16	$1.20
$6.25	$0	$0	$25	$4.69	$6.25	-$1.56
$5.55	40	$0	$50	$4.16	$12.50	-$8.34

Table 2. Price List for WTP when House is Worth $8

Cost	Yes, I choose prescribed burn	No, I do not choose prescribed burn
$0	Yes	No
$2	Yes	No
$4	Yes	No
$6	Yes	No
$8	Yes	No

Table 3. Standard Lottery Task in Gains Domain

Lottery S				Lottery R						
p($24)		p($26)		p($1)		p($50)		EV^S	EV^R	Difference
1	$24	0	$26	1	$1	0	$50	$24	$1	$23
0.9	$24	0.1	$26	0.9	$1	0.1	$50	$24.2	$5.9	$18.3
0.8	$24	0.2	$26	0.8	$1	0.2	$50	$24.4	$10.8	$13.6
0.7	$24	0.3	$26	0.7	$1	0.3	$50	$24.6	$15.7	$8.9
0.6	$24	0.4	$26	0.6	$1	0.4	$50	$24.8	$20.6	$4.2
0.5	$24	0.5	$26	0.5	$1	0.5	$50	$25	$25.5	-$0.5
0.4	$24	0.6	$26	0.4	$1	0.6	$50	$25.2	$30.4	-$5.2
0.3	$24	0.7	$26	0.3	$1	0.7	$50	$25.4	$35.3	-$9.9
0.2	$24	0.8	$26	0.2	$1	0.8	$50	$25.6	$40.2	-$14.6
0.1	$24	0.9	$26	0.1	$1	0.9	$50	$25.8	$45.1	-$19.3

Table 4. Standard Lottery Task in the Loss Domain

with Initial Endowment of $50

Lottery S				Lottery R						
p(-$26)		p(-$24)		p(-$49)		p(-$0)		EV^S	EV^R	Difference
1	-$26	0	-$24	1	-$49	0	-$0	-$26	-$49	$23
0.9	-$26	0.1	-$24	0.9	-$49	0.1	-$0	-$25.8	-$44.1	$18.3
0.8	-$26	0.2	-$24	0.8	-$49	0.2	-$0	-$25.6	-$39.2	$13.6
0.7	-$26	0.3	-$24	0.7	-$49	0.3	-$0	-$25.4	-$34.3	$8.9
0.6	-$26	0.4	-$24	0.6	-$49	0.4	-$0	-$25.2	-$29.4	$4.2
0.5	-$26	0.5	-$24	0.5	-$49	0.5	-$0	-$25	-$24.5	-$0.5
0.4	-$26	0.6	-$24	0.4	-$49	0.6	-$0	-$24.8	-$19.6	-$5.2
0.3	-$26	0.7	-$24	0.3	-$49	0.7	-$0	-$24.6	-$14.7	-$9.9
0.2	-$26	0.8	-$24	0.2	-$49	0.8	-$0	-$24.4	-$9.8	-$14.6
0.1	-$26	0.9	-$24	0.1	-$49	0.9	-$0	-$24.2	-$4.9	-$19.3

Table 5a. Estimated Risk Attitudes from Lottery Tasks

Parameter	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	Constant	0.33	0.06	0.00	0.21	0.44
μ	Constant	3.41	0.67	0.00	2.11	4.71

† p-value=0.76 for test of coefficient value significantly different from 1

Table 5b. Maximum Likelihood Estimate of Risk Attitudes allowing for Demographic Effects

Parameter	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	Constant	0.33	0.06	0.00	0.21	0.44
	Age	-0.00	0.02	0.91	-.03	0.03
	Female	0.14	0.13	0.27	-.11	0.39
	Hispanic	-.05	0.17	0.79	-.38	0.29
	Business	-.01	0.12	0.92	-.25	0.22
	GPAhigh	0.10	0.15	0.48	-.18	0.39
	Works	-.19	0.13	0.15	-.44	0.06
μ	Constant	0.18	0.200.15	0.00	-1.69	0.61

Table 5c. Maximum Likelihood Estimate of Risk Attitudes in the Loss Frame

Parameter	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	Constant	0.34	0.07	0.00	0.21	0.47
λ	Constant	1.12	0.17	0.00†	0.79	1.46
μ	Constant	0.19	0.02	0.00	0.14	0.24

† p-value=0.67 for test of coefficient value significantly different from 1

Table 6. Joint Estimate of Risk Attitude and Subjective Beliefs

Parameter	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	Constant	0.33	0.06	0.00	0.22	0.44
π_B^{safe}	Constant	0.40	0.01	0.00	0.37	0.43
	WTP	.31	0.04	0.00	.23	.39
π_B^{risky}	Constant	0.56	0.01	0.00	0.54	0.58
	WTP	1.00	†	†	†	†
μ	Constant	0.13	0.01	0.00	0.10	0.15
	WTP	0.25	0.05	0.00	0.14	0.35
	Risk	0.18	0.02	0.00	0.15	0.21

† When estimating the probability of the house burning in the risky scenario where the forest has not been treated with prescribed burn, the estimate is too close to the corner solution of 1.0 to give us a reliable standard error.

Figure 1. Histogram Displaying Distribution of Forest that Burned

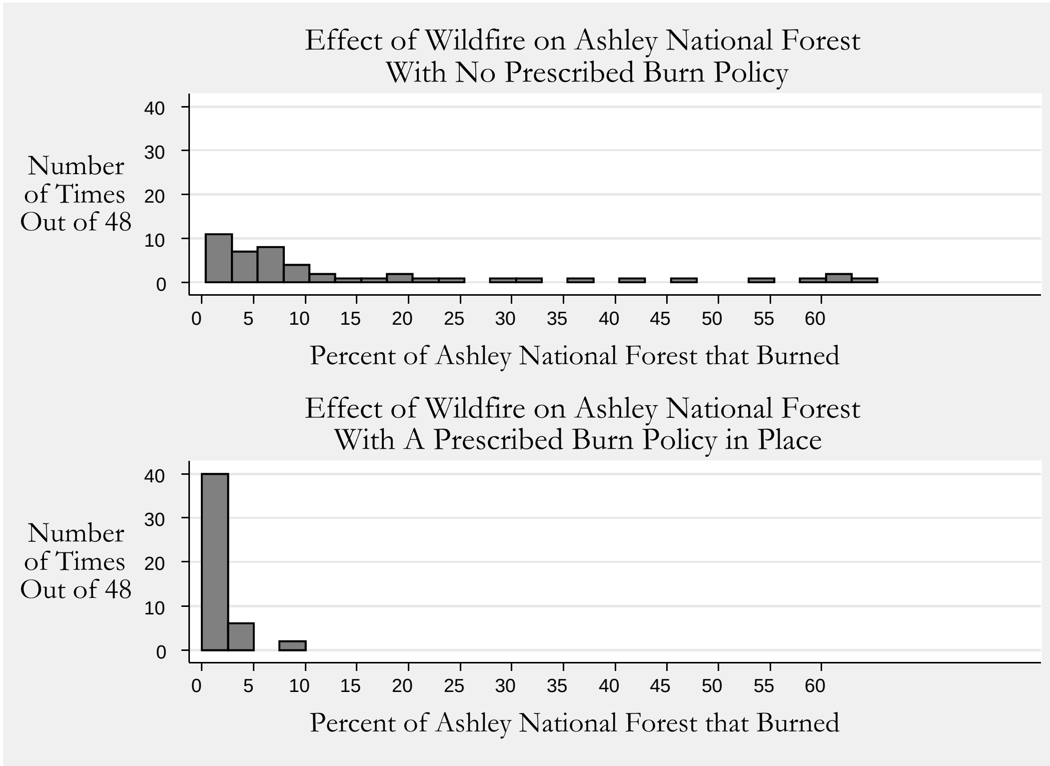


Figure 2. Illustrative Images from VR Interface

Figure 3. Normal and Logistic Cumulative Density Function

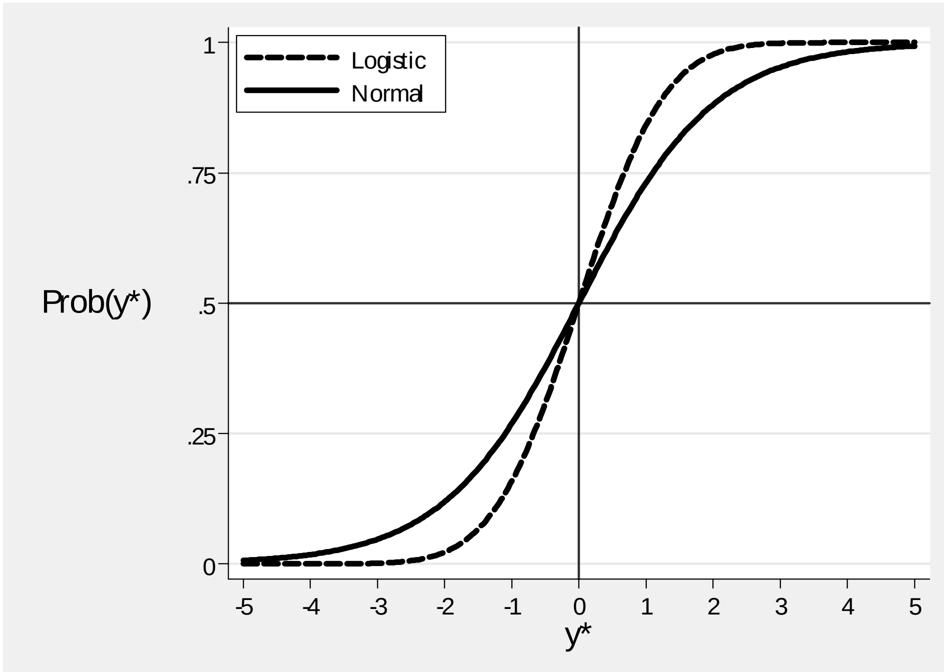
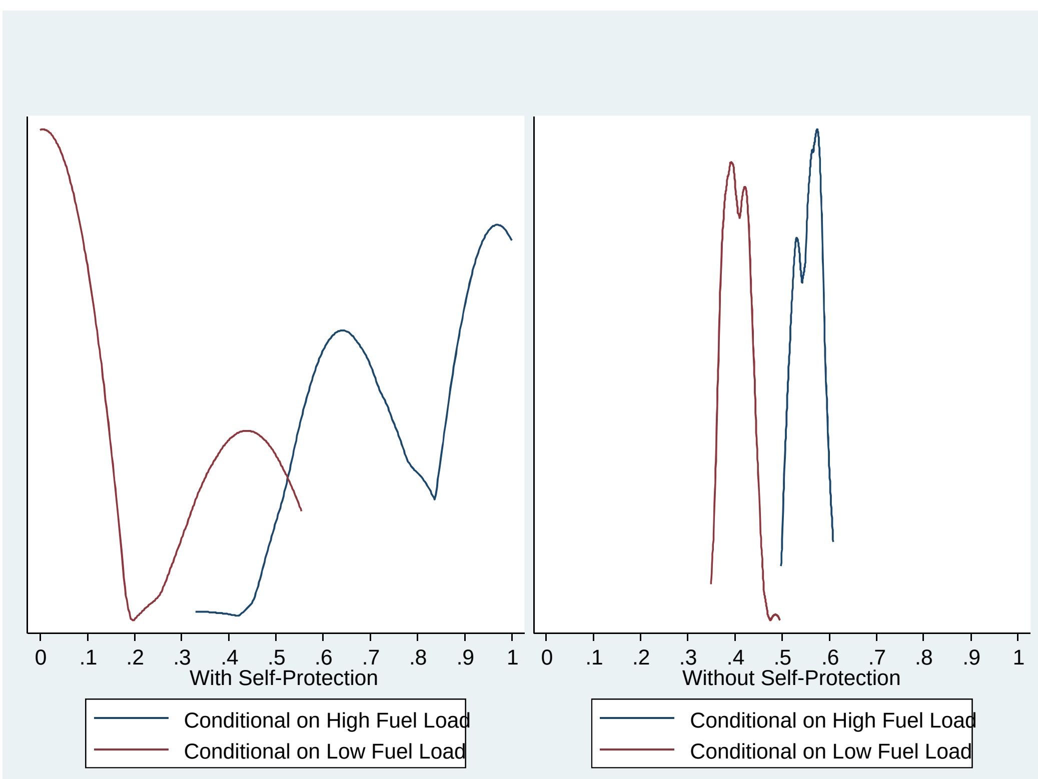


Figure 4. Estimated Subjective Probabilities of House Burning with and without Self-Protection (Fix to look like Fig 3.)



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