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Abstract: Increasing private wildfire risk mitigation is an important part of the larger forest restoration policy challenge. Data from an economic experiment are used to evaluate the effectiveness of providing fuel treatments on public land adjacent to private land to induce private wildfire risk mitigation. Results show evidence of "crowding out" where public spending can decrease the level of private risk mitigation. However, a policy prescription that ameliorates this crowding out is identified. Participants undertake more mitigation when fuel treatments on publicly owned lands are conditional on a threshold level of private mitigation effort and information describing each participant's spending is provided.

I. Introduction

Responding to increasing wildfire risk is an important policy challenge in the Western U.S. and elsewhere (Donovan and Brown 2005). Defined as "the area where houses meet or intermingle with undeveloped wildland vegetation," the wildland-urban interface (WUI) is an area of particular significance (Hammer et al. 2008, pg. 5). Land ownership in the WUI commonly follows a mosaic pattern, where the intermixed public and private land make wildfire risk a collective problem. Referred to as the "mitigation paradox" (Steelman 2007), private landowners and communities frequently fail to undertake sufficient wildfire risk mitigation. The objective of this paper is to use the tools of experimental economics to help design and explore policy packages for confronting the mitigation paradox, and inducing increased private risk mitigation.

Surveys of homeowners indicate that conditions on adjacent properties are an important consideration in mitigation decisions (Brenkert, Champ, and Flores 2005). WUI homeowners recognize the threat of wildfire as a collective problem. Forest management regimes are increasingly accounting for this by providing risk mitigation on publically owned lands adjacent to privately owned lands (U.S. Congress 2000; U.S. Congress 2009). The effectiveness of these types of policies to induce additional private risk mitigation is unclear and motivates this research.

Data from a computerized laboratory experiment (with 244 participants and 2,490 choices) are used to explore the potential response of WUI homeowners to the introduction of policy tools. The experimental design builds on a number of recent studies (McKee et al. 2004; Talberth et al. 2006; Berrens et al. 2007) with the current focus on two potential policies that recognize the prevalent public-private land mosaic in the WUI: (i) a policy where wildfire risk mitigation takes place on surrounding public land; and (ii) a policy where mitigation on surrounding public land takes place *only if* a threshold number of individuals have undertaken fuel reductions. The modeling of participants' mitigation decisions controls for risk aversion and social trust, as well as information provision. In creating a total of six treatment cells, the two policy treatments are compared against a no action baseline case, and then all three settings are evaluated with and without the provision of information on the risk mitigation behavior of other participants.

Results indicate that public spending can have the unintended effect of decreasing the amount of private risk mitigation. However, a policy prescription that ameliorates this crowding out is identified. A policy of providing fuel treatments on public land conditional on a threshold of private risk mitigation while simultaneously disseminating collective information describing each participant's effort is shown to increase participant spending on wildfire risk mitigation.

II. Background and Motivation

The wildfire problem in the Western U.S. and elsewhere is worsening due to a combination of natural and human factors. The WUI is expanding. During the 1990s, the WUI grew in area by 19% and in number of households by 22%, such that in 2000, the WUI represented 11% of the total land area (715,000 km^2) and 38% of all housing units (44.3 million) for the coterminous US (Hammer et al. 2008). Fuel loads have also grown as wildfire has been increasingly suppressed in effort to protect homes situated in the WUI (Kovacs 2001; Donovan and Brown 2005). Combined with long-term drought and accumulating fuel loads the expansion of the WUI has significantly increased the risk of high intensity fires (USDA 2003; Donovan and Brown 2005; Westerling et al. 2006).

As a result, large wildfires are occurring more often and are burning an expanding area. On USDA Forest Service lands for example, average annual acres burned increased from 285,000 from 1970-1986 to 1,000,000 from 1987-2002 (Calkin et al. 2005). The pecuniary costs of wildfire are also rising; annual federal appropriations in the US for wildland fire management activities have increased from an average of $1.2 billion from fiscal years 1996-2000 to an average of $2.9 billion during fiscal years 2001-2007 (Nazzaro 2009). Suppression costs typically account for more than 60 percent of the annual federal costs of wildfire management activities and are growing as well (US Government Accountability Office 2007). These rising costs combined with the recognition of wildfire as natural and beneficial process have lead to growing sentiment that a suppression-centered wildfire policy is unwise (Franklin and Agee 2003; Berry 2007; Donovan and Brown 2007).

Moving away from a costly policy focus on suppression requires the re-introduction of natural fire regimes at a landscape scale (Franklin and Agee 2003; Donovan and Brown 2007), while also targeting fuel treatment and risk mitigation efforts to protect at-risk WUI communities (Harbour et al. 2009). These risk-mitigating efforts include: reducing the volume of fuel in an area, using flame resistant building materials, applying flame retardants, creating strategic breaks in fuel sources, and removing ladder fuels that facilitate fires spreading into the forest canopy (Murnane 2006). Because mitigation can potentially reduce suppression costs in the WUI as well as avoid aesthetic costs associated with wildfire, a change in priorities is underway, increasing the focus on these types of preventative actions (O'Toole 2006; USDA 2006).

Though fuel treatments on public lands are ongoing as a part of the National Fire Plan (USDA and US Department of Interior 2000) and Healthy Forest Restoration Act of 2003 (U.S. Congress 2003), wildfire risk mitigation by government alone is insufficient on three counts. First, a significant amount of forested land (58% in the U.S.) is privately owned (Smith et al. 2004). Second, the scope of wildfire is such that there is simply too much land in need of fuel reductions to be paid for with public funds alone. Recent analyses find that nearly 400 million acres of forestland across the U.S. are characterized as either of "moderate" or "high" risk of catastrophic fire (Power 2006). Juxtaposed against these 400 million acres in need of treatment, the federal government has financed treatments on less than 3 million acres in recent years (Power 2006). Third, inefficient levels of wildfire risk mitigation are expected from individuals in the WUI because of the risk externalities associated with fuel treatments (Crowley et al. 2009). Here, risk externalities (sometimes called adjacency externalities) describe the wildfire characteristic of risk being shared across property lines, and that actions taken to mitigate wildfire risk on one property concurrently reduce the risk of fire in the surrounding area (Konoshima 2008). In this way, wildfire risk mitigation can be thought of as a public good (Busby et al. 2007). Termed the "mitigation paradox," (Steelman 2007) the behavior of individuals confronting shared wildfire risk is consistent with theoretical predictions; private individuals do not undertake a sufficient level of wildfire risk mitigation. This suggests a potential role for policy to induce WUI homeowners to undertake risk mitigation.

In practice, a varied set of policy responses are being implemented, including subsidizing private spending on fuel treatments[1], enacting legislation that marries insurance availability and premiums to risk mitigating behavior (Wallace 2005), and providing education about wildfire risk and fuel treatments (Sturtevant and McCaffrey 2006). This paper focuses on the effectiveness of a specific approach: providing wildfire risk mitigation on public lands that are adjacent to privately owned lands.

A number of collaborative, community-forestry-based management programs have been implemented that fund risk mitigation on public lands that are adjacent to private lands. One notable example is the ongoing federal Collaborative Forest Restoration Program (CFRP) in New Mexico, and potentially at a broader national level the recently-enacted Forest Landscape Restoration Program (FLRP) (U.S. Congress 2000; U.S. Congress 2009). One rationale underlying these programs is that landowners mitigation decisions are increasingly thought to be influenced by the extent of risk mitigation taking place in the surrounding area (Brenkert, Champ, and Flores 2005; Martin et al. 2007). While evaluation of the effectiveness of collaborative, community forest management programs has begun (American Forests et al. 2005; Prante et al. 2007), the potential of fuel reductions on public lands to generate wildfire risk mitigation on adjacent private lands remains largely unknown.

The issue of how to induce private wildfire risk mitigation is attracting increasing attention from researchers. Two lines of work are particularly relevant here: one set of analyses have addressed the issue with theoretical models and the use of numerical simulation (Amacher et al. 2005; Lankoande 2005; Amacher et al. 2006; Shafran 2008a; Crowley et al. 2009), and a second set of studies making use of laboratory experiments

(McKee et al. 2004; Talberth et al. 2006; Berrens et al. 2007; Shafran 2008b). Evidence from both lines of research suggests that policy can be effective in inducing private risk mitigation. However, this is tempered by the observation of policy in some instances crowding out private risk mitigation (McKee et al. 2004; Berrens et al. 2007; Crowley et al. 2009). Although the overall objective of increasing private spending on wildfire risk mitigation remains, identifying policy tools that ameliorate crowding out while also providing public spending on wildfire risk mitigation emerges as another objective.

III. Experiment Design

This section describes the experiment. The experiment took place during the Fall 2007, Spring 2008, and Fall 2008 semesters at the University of Alaska, Fairbanks. Undergraduate student were recruited from across the university as subjects. Upon entering the lab, each subject was randomly assigned a workstation in a carrel consisting of a networked laptop computer, a preamble providing background information on homeowners living in the WUI, and a satellite photo showing an example home situated in the WUI. The experiment began with the proctor reading the preamble aloud as subjects followed along with their hard copies. Once the proctor finished reading the preamble, participants were asked to follow the instructions on their laptops.[2]

Groups of 12 subjects participated in each session. To mirror the relevant features of an environment with intermixed publicly and privately owned land, the 12 participants each represented a WUI homeowner and there were 4 additional parcels of publically owned land. Risk mitigation on these publicly owned parcels was controlled by the experimenter to simulate the policy tools evaluated.

Sessions proceeded as follows. Each participant was endowed with an asset, called their "home asset." Participants earned an income stream in each round based on the value of their "home asset." A random draw took place at the end of each round to determine whether the group experienced a wildfire event. If a wildfire event occurred, each participant's home asset decreased in value, thus reducing a participant's income stream in future rounds. However, participants could engage in activities that reduced risk exposure, and consequently reduced financial consequences of a wildfire event. Sessions lasted 12 rounds but subjects were not informed of the end point.[3] Subjects allocated income earned from their "home asset" among three goods in each round.

The first good available to participants was named "Mitigation," and was intended to represent expenditures on real world risk mitigating processes such as fuel reductions. There are two benefits from the good "Mitigation." First, spending on this good reduces the probability that the group experienced a wildfire event. Second, spending on "Mitigation" reduced the magnitude of the loss participants experienced if a wildfire event occurred. As noted earlier, wildfire risk mitigation in real world situations generate positive externalities. The good "Mitigation" in the experiment is therefore created such that the benefit of a lab dollar spent on the good is accrued not only by the individual spending that lab dollar, but to the group as a whole.

The second good available to participants was called "Insurance," and was intended as a proxy for real world spending on insurance. When a participant spent a lab dollar on "Insurance", they were reimbursed if a wildfire event occurred. Unlike mitigation, the benefit a participant receives from purchasing insurance does not depend on the spending behavior of the rest of the group. For every $LAB a participant spends on “Insurance,” $LAB 16 are added back to the value of their home asset if a fire occurs. Insurance purchases are only good for the current round.

The final good participants chose among was called “Savings.” A subject’s spending on “Savings” did not impact wildfire behavior in the experiment but instead is the principle mechanism by which subjects earned payment for their participation in the experiment. At the conclusion of the experiment, each $LAB that a participant spent on “Savings” is converted into American dollars and awarded to the subject (in cash).[4] The behavior of interest is how participants distributed the income they earned each round among “Mitigation,” “Insurance,” and “Savings” as experimental treatments were introduced.

Wildfire events in the experiment were designed to follow the properties of wildfire in the WUI. Risk mitigation has the potential to reduce the intensity of a fire by reducing the amount of available fuel to burn (Kovacs 2001). Fuel reductions can also reduce wildfire intensity by inhibiting the spread into the forest canopy where fuel is abundant (USDA 2003). Homeowner’s risk exposure is thought to be determined not only by the conditions on their property, but also by the conditions of the surrounding landscape (Finney 2006; Scott 2006). Similarly, the benefits of mitigation not only accrue to the individual but by everyone in the vicinity; mitigation generates a positive externality for the surrounding area. Further, because wildfire risk is shared, the *effectiveness* of risk mitigation also depends upon the conditions on surrounding lands (Shafran 2008a). Though weather and topography cannot be altered by mitigation, reducing fuel loads provides homeowners a way to slow the spread of wildfire (van Wagtendonk 1996; Finney 2001).

In the experiment, the probability of a wildfire events is modeled as a function of the sum of all participants spending on "Mitigation" in the round, the number of participants engaging in mitigation, and the number of rounds that have elapsed since the previous wildfire event (this simulates fuel accumulation in the absence of wildfire). For the experiment, this was parameterized with the following function:

$$\pi = 0.4 + (RE * 0.01) - \left(\frac{N/48}{1 + 60e^{-GMIT/6000}} \right) \quad (1)$$

where π is the probability of a wildfire event occurring, RE is the rounds elapsed since the last wildfire event, N is the number of participants mitigating, and $GMIT$ is the sum of all participants spending on "Mitigation" in the round.[5]

The process is complex and, of course, the participants do not directly observe equation (1). Instead, via the computer interface, subjects can see how much each lab dollar spent on mitigation will reduce risk exposure through trial and error with two "sliders." Subjects drag scrollbars representing the number of participants undertaking risk mitigation and the level of mitigation undertaken by the group, respectively. As participants change their conjecture regarding the group decisions, the projected probability of wildfire and potential losses presented at the bottom right corner of the screen change. Through the use of these sliders the process of wildfire risk mitigation that is characterized by equation (1) is presented. [6]

As with wildfire probability, the severity of the loss in value of their home assets in the event of a wildfire is determined by the sum of all participants spending on "Mitigation" in the round and the number of participants engaging in mitigation. If a wildfire event takes place in a round, equation (2) is used to determine event severity:

$$LOSS = 0.71 - \left(\frac{N/24}{1 + 36e^{-GMIT/3600}} \right) \quad (2)$$

$LOSS$ is the proportion of a participant's home asset value that is lost due to the wildfire, N is the number of participants mitigating, and $GMIT$ is the sum of all participants spending on "Mitigation" in the round. As before, participants use the sliders to form estimates of how spending on "Mitigation" and the number of participants undertaking mitigation will reduce the severity of a potential loss.

$$V_{r+1} = V_r - (V_r * LOSS + INS_i * 16) \quad (3)$$

Where V_{r+1} is the value of a participant's home asset in round $r+1$, V_r is the value of a participant's home asset in round r, $LOSS$ is the proportion of a participant's home asset value that is lost due to the wildfire, and INS_i is the number of $LAB the participant spent on the good "Insurance" in the round.

A factorial experimental design is used; refer to Table 2 for a summary of the treatments. Noted in the previous section, we are interested in how the introduction of the simulated policy of fuel treatments taking place on adjacent public land influences participant behavior. Such a policy is simulated in the experiment by manipulating equations (1) and (2). For treatments where mitigation has taken place on publically owned land, N is increased by 4 to reflect simulated treatments on 4 parcels of public land and $GMIT$ by $LAB 60,000 to simulate $LAB 15,000 of "Mitigation" spending on each of these 4 parcels. Additionally, we examine the influence of making participant spending decisions publically known. In sessions implemented "With Information," participants can view a map on their laptops describing each other's spending in the previous round; this is in contrast to sessions implemented "Without Information."

IV. Data Analysis

In all 22 sessions involving 244 subjects were completed, generating 2,490 decisions for analysis. The econometric analysis assumes that participant behavior with respect to decisions over spending on wildfire risk mitigation in the experiment can be characterized by the following model:

$$Spending = f\left(X_{Treatment}, X_{Non-Treatment-Characteristics}, X_{Attitudinal-Description}, X_{Demographics}\right) \quad (3)$$

where $X_{Treatment}$ is a vector of variables describing the treatment invoked, $X_{Non-Treatment-Characteristics}$ is a vector of variables that control for differences in sessions or rounds not attributed to changes in treatments, $X_{Attitudinal-Description}$ is a vector of variables characterizing participants' responses to a set of questions regarding risk and trust, and $X_{Demographics}$ is a vector of demographic variables.

Success for wildfire policy can be defined in several ways. As a result, the econometric approach uses several models. One possible policy goal is to increase the level of wildfire risk mitigation that WUI homeowners undertake. Proponents of this goal argue that because WUI homeowners accrue much of the benefit of wildfire risk mitigation, policy should focus on shifting more of the corresponding financial burden of providing these treatments to these individuals (O'Toole 2006; USDA 2006). The variable MIT is defined as the number of lab dollars a participant allocates to the good "Mitigation" in a round and is used as the dependent variable in the first of the estimated models. The spending of participant i on MIT is modeled as follows:

$$\begin{aligned} MIT_i &= \alpha + \beta X_{Treatment} + \beta X_{Demographics} + \beta X_{Attitudinal-Description} \\ &+ \beta X_{Non-Treatment-Characteristics} + e_{i,t} \end{aligned} \quad (4)$$

where α represents an intercept term, β represents the estimated coefficients corresponding to the vectors of explanatory variables, and $e_{i,t}$ is an error term.

Another perspective is that the policy objective should be more general, and that alongside increasing mitigation spending should be the goal of increasing private spending on insurance. Though insurance does not speak to the externality aspects of wildfire risk, insurance has obvious benefits at an individual level and public benefits insofar as homeowners with adequate insurance coverage from private markets are less likely to require public assistance in the event of a disaster. The variables INSURANCE and TOTAL are created to reflect this possible goal. INSURANCE is the number of lab dollars a participant allocates to the good "Insurance" in a round and TOTAL is defined as the sum of INSURANCE and MIT within a round. The spending of participant i on TOTAL is modeled with equation (5):

$$\begin{aligned} TOTAL_i &= \alpha + \beta X_{Treatment} + \beta X_{Demographics} + \beta X_{Attitudinal-Description} \\ &+ \beta X_{Non-Treatment-Characteristics} + e_{i,t} \end{aligned} \tag{5}$$

where again α represents an intercept term, β represents the estimable coefficients corresponding to the vectors of explanatory variables, and $e_{i,t}$ is an error term.

Finally, increasing the number of homeowners that undertake mitigation is an additional potential policy goal. The variable MITDV is created to evaluate this objective. MITDV is a dummy variable coded as 1 where a participant undertakes some mitigation and 0 otherwise. Defining X as the groups of variables introduced above in $X_{Treatment}$, $X_{Demographics}$, $X_{Attitudinal\_Description}$, and $X_{Non-Treatment\_Session\_Characteristics}$, and Φ as the standard normal cumulative distribution,[7] the decision of whether to allocate any lab dollars to "Mitigation" is analyzed with random effects probit modeling (6):

$$\Pr\left(MITDV_i = 1 \middle| X\right) = \Phi\left(X\beta\right) \quad (6)$$

For each model, multiple observations are taken from the same session. A concern is that the error terms for such observations are not independent. As a result, random effects modeling is used to analyze the data for each of the three models presented here. By using three models that differ in dependent variables but are similar in the sets of regressors included in the specifications presented here, a framework is constructed to examine the impact of potential policy tools on a varied set of possible objectives.

Table 1 presents a list of the variables used in the modeling and descriptive statistics. The vector $X_{Treatment}$ is made up of a set of dummy variables that distinguish the sessions by the policy regime implemented. Table 2 provides descriptions of the treatments implemented in the experiment. Both of the policy tools are implemented in the experiment in two ways: once “with information” where participants have access to a map on the screen that provides a description of all participants’ mitigation spending in the previous round, and once “without information,” where participants’ mitigation spending decisions are kept private.[8]

Used for comparison against treatments where explicit policy tools are implemented, two variables designate the baseline case where no policy is invoked. BASEWO and BASEW are dummy variables coded as 1 where no policy tool is implemented (without and with information, respectively), and 0 otherwise.

The variable PL_TREATED_WO and PL_TREATED_W are dummy variables coded as 1 for sessions where the experimenter has simulated mitigation taking place on the public land (without and with information, respectively) and 0 otherwise.[9]

The expectation is that simulated policies of wildfire risk mitigation on public land will increase risk-mitigating behavior in the experiment. That is, each of the three measures of success introduced above (the level of spending on mitigation, the level of total protective spending, and the probability that a participant engages in mitigation) are expected to be positively influenced when these policy tools are enacted. Tested against the null hypotheses of no statistically significant influence are the alternative hypotheses that the treatments increase spending on risk mitigation relative to the baseline treatment:

H1: $\beta_{PL\_TREATED\_WO} > 0$

H2: $\beta_{PL\_TREATED\_W} > 0$

The influence of an additional policy tool is considered. Noted earlier, fuel treatments on public land have in some instances been conditional on the commitment exhibited to the problem on surrounding private lands (Prante et al. 2007). An example is the community collaboration requirements of cost-share programs for treating public lands in the federal Collaborative Forest Restoration Program (CFRP) in New Mexico (Prante et al. 2007). The variables POSSIBLE_PLT_WO and POSSIBLE_PLT_W are created to analyze the effectiveness making fuel treatment on public land contingent upon a threshold of private participation. The dummy variables POSSIBLE_PLT_WO and POSSIBLE_PLT_W are coded as 1 for treatments where the public land in the experiment is treated only if six or more participants undertake mitigation in the previous round (without and with information, respectively). Compared against the null of no statistically significant effect, the following hypotheses are tested to analyze the influence of these treatments:

H3: $\beta_{POSSIBLE\_PLT\_WO} > 0$

H4: $\beta_{POSSIBLE\_PLT\_LW} > 0$

Transitioning to the control variables, the vector $X_{Non-Treatment-Characteristics}$ is a set of variables that distinguish session or round characteristics. The variable ROUND_INC is defined as the number of lab dollars a participant receives at the outset of each round to allocate between “Mitigation,” “Insurance,” and “Savings.” The variable WEALTH is defined as the sum of a participant’s “Savings” through the current completed round. Within a session, the time elapsed since a wildfire occurred varies by round and has the potential to influence behavior. The variable FIREPREV is a dummy variable coded as 1 if a fire occurred in the previous round, 0 otherwise.[10] The final two variables included in this category measure the level of interaction a participant exhibits with the software. DIAGRAM is a dummy variable coded as 1 where a participant decided to view a map that provided a more detailed description of the allocation decisions of others than is presented, and 0 otherwise. The variable SLIDER is a dummy coded as 1 if a participant adjusted the slider corresponding to group “Mitigation” to evaluate how the probability and severity of wildfire change with group spending on “Mitigation” and 0 otherwise.

The vector $X_{Attitudinal-Description}$ is made up of variables that capture differences in participant responses to a set of questions after the experiment. Because participants are asked to make decisions that impact probabilities of an uncertain payoff, it is especially important to control for risk preferences. To this end, subjects participated in a widely used risk preference elicitation task (Holt and Laury 2002). In this task, each made a series of choices between two payoff options, one providing a lower payoff with certainty and the other providing either a higher payoff or nothing at varying probabilities. The behavior of interest is at the point where the probability of getting the higher payoff increases such that a participant switches from preferring the sure payoff to the gamble. Using observed choices in this task as a measure of risk preferences, a dummy variable was constructed to sort participants by risk aversion. RISKAV is a dummy variable coded as 1 if a participant displayed risk-averse preferences in the risk elicitation task, and 0 otherwise.[11] Results from this elicitation task are revealed after the wildfire experiment.

In addition to controlling for risk preferences, $X_{Attitudinal-Description}$ also includes a variable that controls for participants' beliefs regarding social capital. The General Social Survey (GSS) is an extensive survey with the objective of collecting data to monitor and characterize trends in American culture.[12] While the GSS has been used in addressing a variety of social science questions, it is increasingly being used in economics analyses involving collective action (Karlan 2005). An index created from responses to a question from the GSS is used here as a proxy for social capital. The question put to participants was the GSS trust question, "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?" [13] Participants select one of six responses to the question that best describes their beliefs. A set of dummy variables has been created here to correspond with these responses. The variable TRUST is a dummy coded as 1 where a participant selects the option most consistent with well developed social capital ("Most people can be trusted"). The dummy variable NTRUST is coded as 1 where a participant selects the response most consistent with a lack of social capital ("You can't be too careful"). These two variables are summed to construct a trust index. The variable T_INDEX is defined as TRUST-NTRUST, so that the variable takes the value of a 1 for trusting participants, -1 for non-trusting participants, and 0 if the participant selected any of the other possible responses to the trust question ("It Depends," "Don't Know," "No Answer," or "Not Applicable").

To evaluate the relationship between social capital (as measured by trust) and mitigation decisions, Hypothesis 5 is:

H5: $\beta_{T\_INDEX} > 0$

The vector $X_{Demographics}$ includes a set of control variables. Participants report demographic information at the conclusion of the experiment. FEMALE is a dummy coded as 1 if a participant identifies themselves as female, 0 otherwise. AGE is the age in years of the participant. The variable EDUCATION is the number of years of formal education.[14] Not to be confused with their income earned in the experiment, the variable ANNUAL_INC is defined as a participant's annual income.[15] HOMEOWNER is a dummy coded as 1 where a participant owns their home, 0 otherwise. $X_{Demographics}$ includes dummy variables that control for political party affiliation. DEMOCRAT and REPUBLICAN are dummy variables coded as 1 for membership in the identified party and 0 otherwise, and OTHERPARTY is a dummy coded as 1 for participants that do not identify their political party as Democrat or Republican, and 0 otherwise.

V. Econometric Results

The discussion of the econometric results is organized by the dependent variable analyzed. Thus the influence of treating publically owned land on the likelihood of a participant undertaking risk mitigation (Models 1A and 1B), the amount participants spend on risk mitigation (Models 2A and 2B), and the amount participants spend on mitigation and insurance summed (Models 3A and 3B) is presented in turn. Estimation results are presented in Table 3. Trimmed and an extended specifications presented for each of the three dependent variables used (MITDV, MIT and TOTAL). Additional specifications were also evaluated, with results qualitatively consistent with the modeling presented here (available upon request). A Hausman test is used to assess the appropriateness of using random effects modeling. For the extended specification using the dependent variable MIT (Model 2B), the chi-squared test statistic is -34.44, indicating that the estimated coefficients in the random effects model are statistically similar to the coefficients from a fixed effects model (known to produce consistent estimates).

Beginning first with Models 1A and 1B, the effectiveness of fuel treatments on publically owned lands to increase the probability that a participant undertakes private risk mitigation is mixed. The estimated coefficients for the variables PL_TREATED_WO and POSSIBLE_PLT_WO are positive but statistically significant for only one specification. This implies that when fuel treatments are simulated on publically owned lands and participant spending is kept private, subjects are not more likely to undertake risk mitigation than in the baseline session. Similarly, the statistically insignificant coefficients for BASE_W indicate that making subject spending public alone did not increase the probability of mitigation. However, simulating fuel treatments on publically owned lands is effective when participant spending is made public. The estimated coefficients for PL_TREATED_W and POSSIBLE_PLT_W are positive and statistically significant in 3 of 4 specifications presented. The results therefore suggest that to effectively increase the likelihood of a homeowner engaging in risk mitigation, fuel treatments should be provided in conjunction with information dissemination. The estimated coefficient for T_INDEX is not statistically significant for this set of models.

The marginal effects presented in brackets in Table 3 show the change in probability of undertaking risk mitigation as the variable of interest changes from 0 to 1. Marginal effects for this model are calculated as:

$$ME = \beta \hat{P}\left(1 - \hat{P}\right) \tag{7}$$

The marginal effects for PL_TREATED_WO and PL_TREATED_W in the extended specification are relatively large, 0.06 and 0.11 respectively.

Of the control variables, the estimated coefficients for WEALTH and AGE are negative and statistically significant, suggesting that participants that have allocated more to "Savings" in previous rounds and older are less likely to undertake risk mitigation. The estimated coefficient for FEMALE is positive and significant indicating that female participants are more likely to undertake mitigation than the base case (males). The coefficients for the remaining control variables are not statistically significant.

As with the results discussed above, the impact of simulated fuel treatments on the level of participant spending is influenced by whether participants are information describing one another's spending. Shown in Models 2A and 2B, the negative and significant coefficients for PL_TREATED_WO and POSSIBLE_PLT_WO (negative but not significant in the trimmed specification) suggest that spending on fuel treatments taking place on publically owned land is replacing private spending. As observed elsewhere (McKee et al. 2004; Berrens et al. 2007), subjects in these sessions spent less on risk mitigation than their counterparts in baseline sessions. Significantly though, disseminating information ameliorates the crowding out. The estimated coefficients for PL_TREATED_W are not statistically significant. This suggests that the addition of information dissemination mutes the negative influence observed in the

PL_TREATED_WO sessions. Further, the estimated coefficients for POSSIBLE_PLT_W are positive and statistically significant. The behavior observed here therefore suggests that information dissemination combined with a policy of making fuel treatments on publically owned lands contingent on private spending can successfully induce private risk mitigation. There is a positive and statistically significant coefficient for T_INDEX, indicating that participants that are more trusting spend more on risk mitigation than their counterparts.

Of the control variables included in Models 2A and 2B, the estimated coefficients for WEALTH, RISKAV, AGE, and FEMALE are negative and significant. The estimated coefficients for DIAGRAM, SLIDER, T_INDEX, HOMEOWNER, and REPUBLICAN are positive and significant. The coefficients for the remaining control variables are not statistically significant for this set of models.

In the experiment, fuel treatments on publically owned lands influence mitigation spending and total protective spending (sum of mitigation and insurance spending) similarly.[16] In Models 3A and 3B, estimated coefficients for PL_TREATED_WO and POSSIBLE_PLT_WO are negative and statistically significant in 3 of 4 models. This indicates that the policy tool has *reduced* private spending. However, when information is provided in conjunction with fuel treatments on public lands, this crowding out is ameliorated. Estimated coefficients for POSSIBLE_PLT_W are positive and significant, indicating that participants undertook more total protective spending when this policy was implemented. As before, the negative and significant coefficient for BASE_W suggests that it is the combination of fuel treatments and information dissemination, rather than fuel treatments or information alone that generates increased mitigation spending. Participants that are more trusting spend higher amounts on mitigation and insurance in sum as shown by the significant positive coefficient for T_INDEX.

Of the control variables in Model 3B, the estimated coefficients for ROUND_INC, FIREPREV, DIAGRAM, T_INDEX, and REPUBLICAN are positive and statistically significant. The estimated coefficients for WEALTH, RISKAV, FEMALE, and EDUCATION are negative and significant. The coefficients for all other variables are not statistically distinct from zero in these models.

VI. Discussion and Conclusions

The objective of this paper is to analyze the effectiveness of providing fuel treatments on adjacent publicly-owned lands at increasing private spending on wildfire risk mitigation. A computerized financial experiment is created where incentives for participants broadly parallels the incentives of WUI homeowners. Using the observed decisions of participants as a policy guidepost, several observations stand out.

Results provide further evidence that policy tools intending to induce WUI homeowners to engage in risk mitigation have the potential to reduce private spending. This effect is identified both for treatments that simulate risk mitigation taking place on public lands irrespective of private behavior and for treatments that offer risk mitigation on public lands conditional upon a sufficient number of individuals undertaking private risk mitigation. Thus, the results suggest that particular care should be taken in policy design to avoid crowding out and reducing private spending on risk mitigation.

The results indentify a specific antidote for this unintended effect: disseminating particular information on the behavior of others sharing the same risk externality.

Behavior in the experiment is influenced by both simulated fuel treatments on public land as well as information provision. Robust across multiple models and specifications, we find that when implemented alongside a policy of fuel treatments on public lands, providing participants with information describing each other's mitigation decisions dampens the degree to which private spending is reduced. Further, when this information is provided along with a policy regime of providing fuel treatments on public lands only if there is sufficient number of individuals engaging in risk mitigation, participants *increase* their spending on wildfire risk mitigation.

Because programs like New Mexico's federal Collaborative Forest Restoration Program (CFRP) [and by inference the newly-initiated, national-level Forest Landscape Restoration Program (FLRP)] are costly to implement relative to standard fuels reduction efforts, whether they generate spillover mitigation on adjacent private lands is an important consideration. That is, adding collaboration, and community-capacity building requirements to fuels reduction projects (or funding opportunities) increases project costs, but may generate important spillover benefits. Shepherd et al. (2009) provide recent evidence that relative to other National Fire Plan fuels reduction projects, CFRP projects in New Mexico exhibit significantly improved social equity effects by better targeting poor communities, with no identifiable loss in risk targeting. This supports the potential of such programs to induce increased private mitigation. However, given that participants in the experiment increase mitigation spending only when information is disseminated in conjunction with providing fuel treatments on public lands that are conditional on private participation, we find both that both aspects of the policy prescription are important.

Providing fuel treatments on publicly-owned lands has a disparate influence on seemingly similar measures of mitigating behavior. This can be observed in the results from sessions where fuel treatments took place without information dissemination (PL_TREATED_WO). Here, the policy tool *increases* the probability that a participant will undertake some mitigation but *decreases* the level of spending on mitigation. It is therefore possible to increase the number individuals engaging in wildfire risk mitigation (e.g., possibly through a demonstration effect) while at the same time decreasing the total level of mitigation (e.g., a possible crowding out effect).. Given the spatial complexities of wildfire risk, it is not obvious whether the negative impact of decreased aggregate expenditures outweighs the positive impact of more people mitigating. Results suggest that policymakers may have to prioritize among policy objectives, weighing the potential gains associated with more individuals undertaking wildfire risk mitigation with costs associated with a reduction in the total level of risk mitigation that takes place.

Finally, the importance of information dissemination in observed mitigation decisions underscores the idea that social factors are critical in analyzing the "Mitigation Paradox." It has been suggested that developing social capital in forest communities is a worthwhile goal of policy, insofar as increased social capital can lead to increased levels of participation and/or private spending on wildfire risk mitigation. Again, this idea appears to be at least part of the motivation behind community forestry-based cost-share programs (e.g., CFRP and FLRP). The observed behavior here that higher levels of trust are a positive determinant of mitigation spending suggests that developing social capital is a worthwhile endeavor for policy.

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Table 1. Variable Descriptions and Summary Statistics (N=2,490).

Variable	Description	Mean(SD)
MIT	The number of lab dollars ($LAB) a participant spends on the good “Mitigation” in a round.	2,463.11 (2,697.71)
INSURANCE	The number of lab dollars ($LAB) a participant spends on the good “Insurance” in a round.	2,486.87 (2,332.82)
TOTAL	Sum of the number of lab dollars a participant spends on total risk reduction for both goods “Mitigation” and “Insurance” in a round.	4,949.98 (3,970.35)
MITDV	Dummy variable coded as 1 if a participant spends at least 1 lab dollar on the good “Mitigation” in a round, 0 otherwise.	0.86 (0.34)
BASE_WO	Dummy variable coded as 1 for sessions where no policy tool is implemented and subjects are not provided information describing the spending of their fellow participants, 0 otherwise.	0.19 (0.39)
BASE_W	Dummy variable coded as 1 for sessions where no policy tool is implemented and subjects are provided information describing the spending of their fellow participants, 0 otherwise	0.19 (0.39)
PL_TREATED_WO	Dummy variable coded as 1 for sessions where the public land has been treated and subjects are not provided information describing the spending of their fellow participants, 0 otherwise.	0.12 (0.33)
PL_TREATED_W	Dummy variable coded as 1 for sessions where the public land has been treated and subjects are provided information describing the spending of their fellow participants, 0 otherwise.	0.17 (0.38)
POSSIBLE_PLT_WO	Dummy variable coded as 1 for sessions where contingent public land is invoked and subjects are not provided information describing the spending of their fellow participants, 0 otherwise.	0.18 (0.38)
POSSIBLE_PLT_W	Dummy variable coded as 1 for sessions where contingent public land is invoked and subjects are provided information describing the spending of their fellow participants, 0 otherwise.	0.14 (0.35)
ROUND_INC	The number of lab dollars a participant receives at the outset of the round.	13,248.81 (2,683.99)
WEALTH	Sum of a participant’s “Savings” from each completed round.	48,281.91 (33,490.30)
FIREPREV	Dummy variable coded as 1 if a fire occurred in the previous round, 0 otherwise.	0.19 (0.39)
DIAGRAM	Dummy variable coded as 1 if during the experiment the participant clicked on the diagram providing more in depth information regarding the spending pattern of the group in the previous	0.24 (0.43)

	round, 0 otherwise	
SLIDER	Dummy variable coded as 1 if during the experiment the participant adjusted the slider that shows how the level of group spending changes the impact of the good “Mitigation,” 0 otherwise.	0.77 (0.42)
RISKAV	Dummy variable coded as 1 for participant’s whose choices in the risk aversion elicitation task indicate risk averse preferences, 0 otherwise.	0.66 (0.47)
TRUST	Dummy variable coded as 1 for participants who when asked the question “Generally speaking, would you say that most people can be trusted or that you can’t be too careful in dealing with people?” selected the response “Most people can be trusted,” 0 otherwise.	0.31 (0.46)
NTRUST	Dummy variable coded as 1 for participants who when asked the question “Generally speaking, would you say that most people can be trusted or that you can’t be too careful in dealing with people?” selected the response “You can’t be too careful,” 0 otherwise.	0.36 (0.48)
T_INDEX	A constructed trust index from responses to the GSS “Trust Question.” T_INDEX=TRUST-NTRUST.	-0.05 (0.81)
FEMALE	Dummy variable coded as 1 if a participant is female, 0 otherwise.	0.40 (0.49)
AGE	Age of a participant.	22.27 (5.23)
EDUCATION	Number of years of schooling a participant has completed.	14.20 (2.45)
ANNUAL_INC	A participant’s annual household income ($).	32,409.64 (21,900.39)
HOMEOWNER	Dummy variable coded as 1 if a participant is a homeowner, 0 otherwise.	0.15 (0.35)
DEMOCRAT	Dummy variable coded 1 if a participant’s political party is Democrat, 0 otherwise.	0.19 (0.39)
REPUBLICAN	Dummy variable coded 1 if a participant’s political party is Republican, 0 otherwise.	0.27 (0.44)
OTHERPARTY	Dummy variable coded 1 if a participant does not identify their political party as Democrat or Republican, 0 otherwise.	0.55 (0.50)

Table 2. Treatment Table.

Treatment name	Land Treatment Policy Tool	Description	Information Describing the Spending of other Participants Provided	Variable Designation	Number of Sessions
T1	None	Baseline, without information: No land treatment policy tool is invoked.	No	BASE_WO	4
T2	None	Baseline, with information: No land treatment policy tool is invoked.	Yes	BASE_W	4
T3	Public land is treated	For each of the four parcels of public land, 15,000 lab dollars are added to the sum of all participants spending on "Mitigation" in the round.	No	PL_TREATED_WO	3
T4	Public land is treated	For each of the four parcels of public land, 15,000 lab dollars are added to the sum of all participants spending on "Mitigation" in the round.	Yes	PL_TREATED_W	4
T5	Public land treated contingent on participation	If at least 6 participants spent at least 1 lab dollar on "Mitigation" in the previous round, then for each of the four parcels of public land, 15,000 lab dollars are added to the sum of all participants spending on "Mitigation" in the round.	No	POSSIBLE_PLT_WO	4
T6	Public land treated contingent on participation	If at least 6 participants spent at least 1 lab dollar on "Mitigation" in the previous round, then for each of the four parcels of public land, 15,000 lab dollars are added to the sum of all participants spending on "Mitigation" in the round.	Yes	POSSIBLE_PLT_W	3

Table 3. Random Effects Regression Results (N= 2,490).

Model:	1A	1B	2A	2B	3A	3B
	Dependent Variable: MITDV		Dependent Variable: MIT		Dependent Variable: TOTAL	
BASE_W	-0.16 (-0.88) [-0.03]	-0.20 (-0.97) [-0.04]	-888.71 (-1.72)*	-1158.49 (-6.67)***	-994.26 (-1.22)	-1092.53 (-4.73)***
PL_TREATED_WO	0.25 (1.18) [0.04]	0.39 (1.74)* [0.06]	-946.68 (-1.68)*	-579.01 (-3.12)***	-1997.14 (-2.26)**	-1558.30 (-6.32)***
PL_TREATED_W	0.76 (3.68)*** [0.11]	0.89 (3.86)** [0.11]	-419.58 (-0.81)	-242.17 (-1.27)	-1167.22 (-1.43)	-822.38 (-3.22)***
POSSIBLE_PLT_WO	0.29 (1.48) [0.05]	0.33 (1.62) [0.05]	-265.66 (-0.51)	-359.51 (-2.10)***	-461.10 (-0.57)	-382.23 (-1.69)*
POSSIBLE_PLT_W	0.35 (1.64)* [0.06]	0.26 (1.14) [0.04]	1027.11 (1.84)*	412.56 (2.13)**	1246.90 (1.42)	715.68 (2.77)***
ROUND_INC	---	1.69e-5 (1.00) [0.00]	---	0.05 (2.23)**	---	0.15 (4.86)***
WEALTH	---	-8.54e-6 (-7.15)*** [-0.00]	---	-0.04 (-25.87)**	---	-0.06 (-30.57)***
FIREPREV	---	0.01 (0.07) [0.00]	---	38.40 (0.29)	---	542.54 (2.91)***
DIAGRAM	---	0.04 (-0.40) [-0.01]	---	362.09 (2.86)***	---	476.66 (2.66)***
SLIDER	---	0.43 (5.59)*** [0.09]	---	366.14 (3.36)***	---	198.88 (1.29)

RISKAV	---	-0.06 (-0.77) [-0.01]	---	-541.73 (-5.56)***	---	-452.02 (-3.30)***
T_INDEX	---	0.05 (1.09) [0.01]	---	161.56 (2.76)***	---	388.86 (4.71)***
FEMALE	---	0.51 (6.27)*** [0.08]	---	-218.98 (-2.28)**	---	-387.66 (-2.87)***
AGE	---	-0.03 (-4.36)*** [-0.01]	---	-58.98 (-5.85)***	---	2.08 (0.15)
EDUCATION	---	0.10 (6.26)*** [0.02]	---	11.36 (0.55)	---	-77.14 (-2.65)***
HOMEOWNER	---	0.16 (1.30) [0.03]	---	494.34 (3.49)***	---	37.77 (0.34)
ANNUAL_INC	---	-2.55e-6 (-1.45) [-0.00]	---	-1.20e-3 (-0.53)	---	-2.64e-3 (-0.83)
REPUBLICAN	---	0.10 (0.11) [0.00]	---	334.40 (2.96)***	---	326.14 (2.05)**
DEMOCRAT	---	-0.13 (-1.30) [-0.02]	---	122.49 (0.99)	---	242.41 (1.39)
CONSTANT	0.94 (7.14)***	0.17 (0.45)	2710.33 (7.39)***	5020.51 (10.30)**	5477.50 (9.51)***	7514.90 (11.01)***
Log Likelihood	-943.72	-842.83	---	---	---	---
Wald Chi squared	---	---	15.51***	1154.53	14.66	1505.66***

Notes: ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively (two-tailed t-tests). Marginal effects presented in brackets

[1] Cost-sharing programs and subsidization of fuel reductions on private lands have been used widely; See USDA (2009); Available July 1, 2009 at: http://www.wildfireprograms.usda.gov/search.html?search=index&&view=type.

[2] The instructions, along with the screen images participants see throughout the experiment are available upon request and can be viewed at http://www.cwu.edu/~prantet/Wildfire_Aux_Docs.pdf.

[3] Some sessions were conducted with fewer participants (10 or 11) when less than 12 were available. The econometric results are not sensitive to the number of participants.

[4] There are four components to participant earnings for the experiment: the sum of a participant's spending on "Savings" for each round, the participant's earnings from the risk elicitation task, and 50% of the participant's asset value at the conclusion of the experiment, and a "show up" payment of five dollars. On average, the experiment lasted one hour and 15 minutes and subjects were paid $31.87 for their participation.

[5] In the experiment, the parameters used in equations (1) and (2) determine the efficacy of a lab dollar spent on "Mitigation" to reduce risk exposure. In real world applications, the efficacy of risk mitigating behaviors to reduce risk exposure varies as local geographies change. The parameters used here are therefore not intended to reflect the effectiveness of risk mitigation for all WUI applications but rather were chosen for tractability in the experiment.

[6] In addition to the "sliders," several other steps are taken to facilitate participant understanding. First, before the primary experiment, subjects participate in a tutorial on the mechanics of the "sliders" (see Screen 3 in the Auxiliary materials located at http://www.cwu.edu/~prantet/Wildfire_Aux_Docs.pdf. Second, two practice rounds take

place before participants choices are tied to payoffs. Third, there are buttons near each of the sliders labeled “What’s this?” that participants can click on for additional explanation about a feature of the experiment (see Screen 16 in the Auxiliary materials).

[7] For completeness, the data has also been analyzed with logit probability models. These results are similar and available if requested.

[8] To see how this information is presented, refer to the Auxiliary materials located at http://www.cwu.edu/~prantet/Wildfire_Aux_Docs.pdf.

[9] This is incorporated into the equations (1) and (2) by increasing N by 4, to reflect simulated treatments on 4 parcels of public land and $GMIT$ by $LAB 60,000 to simulate $LAB 15,000 of “Mitigation” spending on each of these 4 parcels.

[10] The variable FIREPREV is coded as 0 for the first round of the session.

[11] Risk averse preferences are defined here as preferring the uncertain payoff only once the probability of receiving the higher payoff reached 0.6.

[12] This description of the GSS, and additional information describing the GSS is available at: http://www.norc.org/GSS+Website, accessed April 30, 2008.

[13] Not presented here, alternative modeling included two additional GSS questions: the helpful question, “Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?” and the fairness question, “Do you think most people would try to take advantage of you if they got the chance, or would they try to be fair?” Results on these variables were not statistically significant.

[14] For both AGE and EDUCATION, several respondents did not respond. The mean age and education level for all participants was used for these observations

[15] Participant's reported income by indicating which among 10 categories described their income group. To reduce the expanding number of indicator variables used, these responses were converted to continuous data by entering for each observation the midpoint from its respective income category. As with AGE and EDUCATION, non-responses were replaced with the mean income.

[16] Given similarities in the experimental goods considered, the potential exists for the policy tools to influence the *proportion* of total spending characterized as mitigation. Participants may shift spending between insurance and mitigation in response to changing policy regimes. An additional set of log-odds models (similar to Talberth et al. 2006) was used to examine the influence of each policy tool on the proportion of total spending directed to mitigation. The estimated coefficients for each policy tools are for the most part not statistically significant. These results are available upon request