THREE ESSAYS ON WILDFIRE ECONOMICS AND POLICY

By

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To the Faculty of Washington State University:

The members of the Committee appointed to examine the dissertation of MARIAM D. LANKOANDE find it satisfactory and recommend that it be accepted.

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Chair
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ABSTRACT

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This dissertation, which consists of three independent but related papers, investigates alternative management strategies to mitigate the risk of wildfire occurrence and to minimize the risk of financial losses from wildfires.

In the first essay, we discuss the economic tradeoffs between different fire mitigation techniques such as suppression and fuel treatment. We develop a nested rotation model to examine optimal fuel treatment timing in the context of a forest environment with both timber and non-timber values-at-risk. Simulations are performed for a ponderosa pine forest and discussed with a focus on three important aspects of wildfire management: 1) the economic tradeoffs between fuel treatments, suppression, and timber harvest 2) the effects of public wildfire suppression on private fuel management incentives, 3) externality problems when non-timber values-at-risk such as wildland-urban interface property is not accounted for in private fuel management decisions.
The second essay provides an empirical basis for a widely used economic model of wildfire management that seeks to minimize the sum of suppression costs and economic losses from wildfires, the cost plus net value change model of fire suppression (C+NVC). We estimate a model of suppression productivity for individual fires, where suppression productivity is measured in terms of the reduction in the estimated market value of wildfire losses. Estimation results show that at the margin, every dollar increase in suppression costs reduces resource damage by 12 cents, while each dollar invested in pre-suppression reduces suppression expenditures by 3.76 dollars. These results suggest that there is an over-allocation of fire management funds to suppression activities relative to prevention measures in terms of cost-effectiveness.

The third essay addresses the issue of wildfire insurance and risk mitigation policy in wildland-urban interfaces, where rapid economic development has become a growing policy concern. We investigate the effectiveness of a government subsidy and mitigation based insurance contracts at discouraging migration into the wildland interface and at inducing incentives for risk mitigation. We construct a model of the individual migration decision, where the individual maximizes expected utility defined over attributes of locations including cost of insurance and mitigation, wildfire damage, and the availability of a subsidy for reducing wildfire risks through fuel management. Our analysis shows that standard insurance policies provide inefficiently weak incentive for wildfire risk mitigation by offering a low insurance premium to high-risk landowners. We find on the other hand that in the presence of optimal government subsidy, contingent contracts provide an efficient solution where a homeowner chooses a mitigation level that maximizes social benefit and insurers provide actuarially fair contracts such
that each individual is offered a premium of the exact value of her wildfire risk.

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CHAPTER I
FUEL MANAGEMENT AND SUPPRESSION AS COMPLEMENT FOR WILDFIRE RISK MITIGATION: A NESTED ROTATION MODEL APPLIED TO PONDEROSA PINE FOREST

1. Introduction

A century-long policy of intensive wildfire suppression has contributed to substantial accumulation of vegetative fuel loads and wildfires of increasing severity in many forest environments (Ingalsbee 2000, Prestemon et al. 2001). Over the last three decades, forest managers and fire researchers have increasingly called for greater emphasis on management of vegetative fuels for wildfire risk mitigation (Stephens 1998, Pollet and Omi 2002, Hoff and Omi 2003, Rideout 2003, Martinson and Omi 2003). In response, the Healthy Forests Restoration Act of 2003 (HFRA) includes substantial emphasis on fuels management to address forest health and wildfire concerns. In principle, the Act calls for increases in the use of prescribed fire and mechanical thinning to reduce fuel loads, and it dictates that these efforts should concentrate primarily on the wildland urban interface. The precursor to the HFRA, George W. Bush’s Healthy Forest Initiative, sparked off heated debate because environmental groups argued that it was an attempt to justify and facilitate commercial logging on federal land.

One of the major hurdles for addressing the controversy over the Healthy Forest Initiative is a poor scientific understanding of the effectiveness of fuel management for wildfire risk mitigation and of the economic and physical relationships between fuel management and suppression as wildfire risk mitigation alternatives. The theoretical economic foundations of
wildfire suppression were initially developed early in the twentieth century as a simple cost minimization problem (Sparhawk, 1925), and this cost-minimization perspective has been incorporated conceptually into the decision-making process of wildfire suppression efforts. However, the empirical understanding of the productivity of suppression for reducing damage is weak to nonexistent. The scientific understanding of fuel management for wildfire risk mitigation is also still at an early stage of development, especially research regarding political economy, property rights, and incentives for fuel management (Hesseln 2000). The relative effectiveness of commercial logging, as a means of mitigating wildfire risk is unclear, especially in comparison to prescribed fire and pre-commercial thinning as alternatives (Carey and Schumann 2003, Sparhawk 1925, Stone et al. 2004). Finally, the economic relationship of fuel management and suppression as complements is only just now beginning to receive significant attention in the economics literature (Botti et al. 2004, Omi 2004, Prestemon et al. 2004).

We contribute to this nascent literature on the economic relationship between suppression and fuel management by developing a dynamic model and simulations to characterize and illustrate the fundamental tradeoffs involved in wildfire risk mitigation. We model fuel management as a timing problem in which fuel treatment rotations are nested within a timber harvest rotation. Wildfire occurrence is a stochastic variable whose probability distribution is altered by fuel treatment and truncated by harvest. The costs of wildfire include timber and non-timber property damage, as well as wildfire suppression costs. Choice variables in the model include the number and timing of fuel treatments, the timber harvest date, and wildfire suppression effort. We parameterize the general model and perform simulations for a representative ponderosa pine forest, a prevalent forest type in the Western United States in low
elevation areas that are often populated by humans. The model allows a formal representation of
the economic tradeoffs between wildfire damage and suppression, fuel treatment, and harvest.
Moreover, it facilitates analytical and numerical comparative statics analysis for changes in
various model parameters, such as exogenous increases in values at risk, suppression costs, and
fuel treatment costs.

We apply the model to examine some important institutional issues for private and public
landowners and managers in wildfire prone environments. First, individual private landowners
face relatively weak incentives for fuel management and suppression because they do not accrue
all the benefits of these efforts; some benefits accrue to neighbors in the region because wildfire
moves through a landscape regardless of property boundaries. This externality problem is
particularly acute in highly fragmented and high value areas such as at the wildland-urban
interface. Second, because wildfire suppression is generally provided by public agencies, the full
cost of wildfire are not accrued by landowners and are not economically tied to fuel management
activities. Also, public land managers arguably face incentives that induce too much investment
in suppression and too little in fuel management (Ingalsbee 2000, O’Toole 2002).

Numerous studies have focused on the economics of timber harvest under the risk of total
destruction of forest value based on Faustmann-type analyses (Martell 1980, Routledge 1980,
Reed 1984, Reed and Errico 1985 1986, Reed 1987, Thorsen and Helles 1998). Of these, our
approach is perhaps most closely related to Reed (1987). Reed uses an optimal control
framework to examine optimal timber rotation and continuous wildfire protection for a forest
stand subject to sudden destruction by fire. Along different lines, Yoder (2004) examines the
optimal rotation of prescribed fire treatments for reducing wildfire risk and providing forage or
other benefits. Our approach is unique in three ways: First, we present a model generic enough to make use of the two generic forms of fuel treatment (thinning and prescribed fire). Second, although the treatment of fuel management as a rotation problem is similar in spirit to Yoder (2004), the analytical and numerical implementation of the nested rotation problem is substantially different and provides new insights into the relationships between treatments, harvest, and suppression. Third, we formally examine the impacts of externalities and public firefighting suppression on private fuel management incentives.

The next section describes the theoretical model and optimization routine. In section three the results of the simulations are presented and discussed. Section four concludes with some policy implications.

2. Wildfire Management as a Nested Rotation Problem

Consider a forest stand that is managed to maximize the expected net present value of an infinite series of harvests under the risk of wildfire. At any point in time during the maturation of the forest stand, a wildfire might occur that can impose damage on both the forest stand and other property such as homes. The time-path of wildfire risk (referred to as the wildfire return distribution in the fire sciences literature) is affected by fuel management interventions. In the event of a pre-harvest wildfire, the extent of damage can be reduced by suppression effort. Hence, control variables include the number and timing of fuel management interventions, suppression effort in the event of a wildfire, and a timber harvest date.

Suppose that the timber rotation can be ended in one of two ways: by harvest, or by a wildfire, after which a salvage harvest is performed followed by replanting. Following Reed
(1984), the duration of a rotation can then be thought of as a random variable whose distribution is censored at the planned harvest date. This wildfire return distribution is affected by intra-harvest fuel management interventions. Let \( T_n = [T_1, T_2, ..., T_n]' \) be a \( n \times 1 \) vector of planned action dates. The last element, \( T_n \) is the planned harvest date, and the previous elements \( T_i \) for \( i < n \) are fuel management intervention dates. Every fuel management intervention \( T_i \) has the effect of setting the fuel load back to an initial state, thus shifting the fire return distribution out by the amount of time since the last fire or intervention. Figure I-1 illustrates the probability density function and cumulative density function for wildfires with and without fuel management interventions. Below, we develop the wildfire return distribution conditional on fuel management interventions.

Let the “natural” wildfire return density function (as if it were uninterrupted by management interventions or harvest) be denoted \( f(x) \), which satisfies the requirements of a probability density function for \( x \in \mathbb{R}^+ : f(x) \geq 0 \forall x > 0 \) and \( \int_0^\infty f(x)dx = 1 \). The associated cumulative distribution function for wildfire occurrence in the absence of fuel management or harvest is \( F(x) \), so that \( F(T_i) = \text{Prob}[x < T_i] \). Let \( S(T_i) = \text{Prob}[x \geq T_i] = [1 - F(T_i)] \) denote the survival function evaluated at intervention \( i \), which equals the probability of applying intervention \( i \) of \( n \) prior to a wildfire event.\(^1\) The probability of a wildfire occurring prior to each successive intervention is the recursive conditional set

\(^1\)The following framework follows the engineering literature on reliability and maintenance. See Kececioglu (1991) for an example of a more general treatment.
\[
F(T_1) = \int_{0}^{T_1} f(x)\,dx = 1 - S(T_1)
\]
\[
F(T_2) = S(T_1) \int_{T_1}^{T_2} f(x - T_1)\,dx = S(T_1)F(T_2 - T_1)
\]
\[
F(T_3) = S(T_2) \int_{T_2}^{T_3} f(x - T_2)\,dx = S(T_2)F(T_3 - T_2)
\]
\[
\vdots
\]
\[
F(T_n) = S(T_{n-1}) \int_{T_{n-1}}^{T_n} f(x - T_{n-1})\,dx = S(T_{n-1})F(T_n - T_{n-1}).
\]

Where the vector \( T_i = [T_1, T_2, \ldots, T_i] \) (in boldface) represents the dates of all interventions up to the \( i^{th} \) and \( T_i \) (no boldface) represent the date of \( i^{th} \) intervention. The wildfire return distribution is censored at \( T_n \), and the probability of reaching harvest without a wildfire is \( S(T_n) = 1 - F(T_n) \).

The expected net present value of a timber rotation is made up of two primary components:

- The costs of fuel management interventions prior to harvest or wildfire (equation 2 below). \(^2\)
- The net benefits accrued at the end of the rotation, which may be ended by wildfire or harvest (equation 3 below). \(^2\)

The cost of a fuel treatment \( w \) is accrued at the time of each respective intervention, but a treatment will be performed only if a wildfire has not occurred prior to the planned treatment date, and only if one or more fuel treatments are optimal (that is, if \( n > 1 \) is chosen). Given that an intervention \( i \) is carried out, the discounted cost is \( e^{-rT_i}w \), and the probability carrying out the intervention is \( S(T_i) \). The discounted expected value of intervention costs for one timber rotation can be written as

\(^2\) Other operating costs are suppressed to simplify analyses but would not change results
\[
E[C] = I_{n>1} \left[ \sum_{i=1}^{n-1} e^{-rT_i} S(T_i) \right]
\]  
(2)

Where \( I_{n>1} \) is an indicator variable that takes the value 1 if \( n > 1 \) and zero otherwise.

Now consider the benefits and costs that are accrued at the end of the rotation, which we will denote \( Y \). Because the fire return distribution is censored at \( T_n \), the expected net present value of \( Y \) can be written concisely as

\[
E[Y] = E[Y | x < T_n] + E[Y | x = T_n].
\]  
(3)

Let the function \( V(t) \) denote the stumpage value of timber at any point in time since the end of the last rotation. For simplicity we assume that the stumpage value depends only on stand age (so that fuel treatments do not affect the growth or quality of standing timber), and we ignore replanting costs.\(^3\) If the harvest date \( T_n \) is reached without a wildfire event \( (x = T_n) \), the full value of timber \( V(T_n) \) is recovered at harvest. Thus, the expected value from harvest at the planned date (the second element in equation 3) is

\[
E[Y | x = T_n] = e^{-rT_n} V(T_n) \times \text{Prob}[x = T_n] = e^{-rT_n} V(T_n) S(T_n).
\]  
(4)

If a wildfire occurs prior to the planned harvest date \( (x < T_n) \), suppression effort \( s \) is exerted to reduce the fraction of value lost to the fire, and a salvage harvest for the remaining timber value is performed immediately.\(^4\) Let suppression effort be denoted \( s \) with marginal cost \( \tau \). In the

\(^3\)Both of these simplifications are easily incorporated into the model, but clutter analytical results and are not of central interest in this paper.

\(^4\)There are other possible ways to model timber value loss and the timing of timber value accruals. If the fire damage is not uniform, such as if it completely destroys one part of the stand but leaves the remaining fraction unharmed, the manager may leave the remaining timber to grow until the planned timber harvest date \( V(T_n) \). A complication with this scenario in the context of numerous timber rotations is that each time a fire occurs, the initial stand is effectively split by the fire into two stands of separate ages. Over the course of many rotations and many fires, the stand could be atomized into many small stands of various ages. For simplicity, this issue is not modeled.
event of a wildfire, the fraction $g(s)V(x)$ is lost, so the remaining value is $(1 - g(s))V(x)$. The function $g(s)$ can be thought of as a suppression productivity function, with first and second derivatives $g'(s) < 0$ and $g''(s) > 0$.

Non-timber values can be very important in the context of wildfire management, especially in the Wildland Urban Interface. For expediency in simulating the consequences of externalities on risk mitigation decisions, we treat non-timber damage as distinct from timber losses. Let $D$ represent non-timber values-at-risk from a wildfire, such that $D$ is the total replacement value of non-timber property that would be lost given a wildfire and no suppression effort $(s = 0)$. We assume that suppression productivity is the same for both timber and non-timber values, so that total property losses for a given suppression level are $g(s)(V(t) + D)$. We also assume that the non-timber property is replaced immediately after the fire. Putting the above elements together, the net value accrued if and when a wildfire occurs before harvest is

$$h(x, s) = V(x) - g(s)(V(x) + D) - \tau s.$$  \hspace{1cm} (5)

Given an interest rate of $r$, the expected net present value of the rotation at the end of each successive stage $T_i$ is

$$E[Y \mid 0 < x < T_i] = \int_0^{T_i} e^{-rx} h(x, s) f(x)dx$$

$$E[Y \mid T_i < x < T_{i+1}] = S_i \int_{T_i}^{T_{i+1}} e^{-rx} h(x, s) f(x - T_i)dx$$

$$E[Y \mid T_{i+1} < x < T_{j}] = S_j \int_{T_{i+1}}^{T_{j}} e^{-rx} h(x, s) f(x - T_{j})dx$$

$$\vdots$$

$$E[Y \mid T_{n-1} < x < T_n] = S_{n-1} \int_{T_{n-1}}^{T_n} e^{-rx} h(x, s) f(x - T_{n-1})dx.$$  \hspace{1cm} (6)

and letting $T_0 = 0$, 

Equation 7 is the first term in equation 3. The expected net present value of a single rotation equals equation 3 minus equation 2. Following Reed (1984), Englin et al. (2000) and others, the expected net present value of an infinite series of rotations is

\[
E[\text{NPV}] = \frac{E[Y] - E[C]}{1 - E[e^{-rT_e}]}
\]

where \( E[e^{-rT_e}] \) is the expected discount factor such that

\[
E[e^{-rT_e}] = \sum_{i=1}^{n} \left[ S(T_{i-1}) \int_{T_{i-1}}^{T_i} e^{-r(x + T_{i-1})} f(x-T_{i-1})dx \right] + e^{-rT_e} S(T_n).
\]

where \( S(T_i) \) are defined in equation 1 and \( S(T_0) = 1 \). The expectation on the discount factor for the series of infinite rotations is necessary because the rotation length itself is a random variable.

Given the necessary and sufficient curvature conditions in the economic region of the choice set, maximization of objective function (8) requires jointly maximizing over \( n \) choice variable, with \( n - 1 \) pre-harvest fuel management interventions, harvest (the \( n^{th} \) action), and the expected suppression effort. Because the number of choice variables is endogenous, solving the optimization problem is performed with a two step process: 1) conditional optimization for a set of feasible \( n \), and then 2) selecting the \( n \times 1 \) vector that provides the highest expected net present value.

**2.1 Selected analytical results**

For illustration, consider the first-order conditions for the case of \( n = 2 \). The landowner chooses the intervention schedule \( T_2 = [T_1, T_2] \), and the expected suppression effort \( s \).
corresponding to $n = 2$. We begin by characterizing the analytical first-order conditions for the case in which the timber owner faces all costs and benefits. We then briefly discuss two extensions of the model: 1) the case in which some wildfire damage is external to the timber owner’s decision process, and 2) the case in which suppression is provided by a public agency rather than the timber owner.

For clarity and intuition of the following analytical results, we temporarily assume a planning horizon of just one timber harvest rotation. The results are intuitively similar for an infinite series of timber harvests, but the analytical first-order conditions are complicated by elements that amount to Faustmann-like land rent components.\(^5\) This assumption is dropped later (the simulations are based on an infinite set of timber harvest rotations).

In general, the first-order conditions for a choice variable $z \in [T_1, T_2]$ is

\[
\frac{\partial E[Y | 0 \leq x < T_1]}{\partial z} + \frac{\partial E[Y | T_1 \leq x < T_2]}{\partial z} + \frac{\partial E[Y | x = T_2]}{\partial z} - \frac{\partial E[C]}{\partial z} = 0
\]

(10)

The first-order condition for suppression is

\[
\int_0^{T_1} e^{-\tau} f(t) h_t(t, s) dt + S(T_1) \int_0^{T_1} e^{-\tau(t+T_1)} f(t-T_1) h_t(t, s) dt = 0,
\]

which is satisfied if

\[
h_t(t, s) \equiv -g_s[V(t) + D] - \tau = 0.
\]

(11)

This first-order condition implies that the marginal benefit of suppression in terms of damage foregone equals the marginal cost of suppression whenever a wildfire occurs.\(^6\)

The first-order condition for fuel management is slightly more complex. Assuming (as

\(^5\)The analytical results for an infinite series of timber rotations are available from the authors.

\(^6\)This first-order condition is the same for an infinite series of rotations as well.
we do in the simulations below) that a fuel management intervention restores the wildfire probability (at intervention time) to zero, the first order condition can be written as:

\[
\int_{T_1}^{T_2} e^{-rT} h_t(x,s) \left[ (S'(T_i) - rS(T_i)) f(t-T_1) - S(T_i) f'(t-T_1) \right] dt \\
- e^{-rT_1} \left[ h_t(T_1,s) + w(rS(T_1) - S'(T_1)) \right] = 0
\]  

(12)

The first line of equation 12 corresponds to the marginal net gains from shortening the time between the fuel treatment and harvest. The second line corresponds to the marginal gains from extending the time until the first fuel intervention, which includes the present value of the change in the probability of expending \( w \), and the marginal gains in \( h(t,s) \) prior to \( T_1 \).

Finally, harvest is performed when the expected marginal increase in timber value from further growth equals the total expected marginal cost of waiting. Assuming again that the risk of damage from wildfire drops to zero at harvest, the first-order condition is:

\[
\left\{ e^{-rT_1} S(T_1) f(T_2-T_1) h_{T_2}(T_2,s) \right\} + \left\{ S(T_1,T_2) \left[ V'(T_2) + V(T_2)(S_{T_2}(T_1,T_2) - r) \right] \right\} = 0
\]  

(13)

The first element in braces is the marginal net present expected benefit of delaying harvest corresponding to the case in which an intervening wildfire occurs (\( \partial [Y \mid T_1 < x < T_2] / \partial T_2 \)). The second element in braces is the marginal expected benefits corresponding to harvest prior to a wildfire event (\( \partial [Y \mid x = T_2] / \partial T_2 \)).

2.2 Extensions: fuel-related externalities and public suppression

Two important aspects of the fuel management problem is that timber owners or managers often do not face the full costs of their contributions to wildfire risk to neighboring property, nor do they pay the full price of suppressing wildfires to which their vegetation has
contributed, because fire suppression services are generally provided for and funded through public agencies.

**Non-timber damage as an externality.** To consider the effects of external wildfire damage, we choose a simple alternative for simulation comparisons that can be a reasonable representation of the wildland-urban interface. Suppose that the timber owner faces all of the timber losses associated with wildfire, but none of the non-timber values at risk, such that $D$ might represent the value of homes in nearby wooded residential neighborhoods. Then the timber owner will make decisions about fuel management, harvest and perhaps suppression (if he or she were paying for it) as if $D$ were equal to zero, even if it is not. Resource allocation decisions for this liability structure can then be compared to the case where the landowner is liable for all costs, including nonzero $D$.

**Public rather than private suppression.** The second case, where timber owners do not pay for suppression, can be examined by making two modifications to the forest owner’s optimization problem. First, the suppression cost term $\tau s$ must be removed from $h(x,s)$ (equation 5), because the timber owner no longer pays these costs. Second, the landowner makes fuel management decisions based on the expectation that suppression will be publicly provided if a fire occurs. We account for this expectation by assuming that in the event of a fire, public suppression will be provided at an optimal level such that it satisfies first-order condition (11), conditional on the forest owner’s pre-fire private fuel management decisions. This first order condition is therefore added as a constraint to the timber owner’s optimization, which, again, is
represented by equation (8) but with $\tau_s$ removed from the second line. Thus, public suppression levels are second best in the sense that it is optimal given preexisting (suboptimal) fuel management outcomes by forest owners. It should be noted that it is highly unlikely that wildfire suppression activities satisfy first-order condition (11). They have almost unlimited but non-reallocable budgets for suppression, which would likely lead to over-suppression (O’Toole 2002). There are a number of other incentive issues lurking within this problem as well, but we use first-order condition (11) as the constraint as a simple illustrative assumption.

3. Simulations specification and results

For simulation, we parameterize our model to approximate ponderosa pine forest of the inland northwest region. We choose a ponderosa pine environment both because it is a common fire-prone environment with substantial human populations (Pollet and Omi 2002), and because there is relatively more known about ponderosa pine fire ecology compared to most other forest types. The specification is based on a per acre basis, but it is important to recognize that the structure and specification of any fuel management and wildfire system such as this is likely to be highly dependent on stand size.

To represent the growth in value of ponderosa pine timber, we use the modified Weibull function $V(t) = A(1-e^{-a t^b})$ described in Yang et al. (1978), where the coefficient $A$ represents the stumpage value of the timber. Using a set of data collected by the Pacific Southwest Research Station and published in Oliver and Powers (1978), we estimated the growth function $V(t) = 128000(1-e^{-0.0005t^2})$, given a site index 80 and a spacing of 10 feet. For the fire return interval representing wildfire probabilities, we use a Weibull distribution with location, scale,
and shape parameters of \( a = 0.001, b = 30, c = 2 \), respectively, which is generally consistent with estimated historic fire return intervals for this forest type. (see Smith and Fischer (1997) for further discussion). These parameters result in a probability density function of 
\[
f(t) = 0.002te^{-0.001t^2}
\]
and a cumulative distribution function of 
\[
F(t) = 1 - e^{-0.001t^2}.
\]
The mean fire return interval for this distribution is approximately 26.6 years.

The productivity of suppression is defined in terms of the fraction of potential damage saved. Based on preliminary regressions using the National Interagency Fire Information Database NIFMID (2004) and simulation model calibration, we use a suppression production function 
\[
g(s) = e^{-0.5s},
\]
where suppression effort \( s \) is defined such that the fire suppression costs per acre is \( \tau = 295 \) Schuster et al. 1997). Accordingly, the per acre cost of one fuel treatment intervention is set at \$130 for U.S. Forest Service region 5, which corresponds to the area where the data were collected (see Schuster et al. (1997) for further discussion). Finally, the interest rate \( r \) is set at 0.05, and non-timber values at risk \( D \) are set to 100,000.

The numerical results for six management strategies are shown in Table 1-1. The simulations were performed using the software Mathematica (Wolfram Research 2002). For each case, the timing and number of interventions, the expected level of suppression given a wildfire, the harvest date, and expected net present values to both the timber owner and to society as a whole are shown. The difference between the timber owner’s present value of expected net benefits and society’s is the expected net present value of total external costs.

Cases 1 through 4 are based on the assumption that the timber owner pays for suppression as if it were a part of operating expenses. Cases 4 and 5 assume publicly provided suppression as discussed above. Cases 2 through 4 and 6 show the effects of restricting the use of one or more
management alternative to zero. For each case, two sub-cases are shown: one in which the timber owner pays for non-timber damage, $D$, and one in which he or she does not. This comparison is important, because apart from some special cases, landowners are not generally liable for wildfires that move off their land onto the land of others.

A couple of general characteristics of the results in table 1-1 are worth noting. First, in all cases, fuel intervention intervals shorten over time within the harvest interval because the value of timber is growing and therefore the values at risk are higher later in the timber rotation. Second, it should be no surprise that the timber owner’s private net present expected value is higher when he or she is not responsible for either non-timber value $D$ or suppression costs, but the social net present expected value is lower due to the poor private timing of actions. Finally, the rotation lengths vary, but are not inconsistent with ponderosa pine rotations in similar environments (Fiedler et al. 1988)

### 3.1 Private suppression

In Case 1, all management options are performed, and suppression costs are borne directly by the timber owner. The results in table 1-1 show that the expected net present value of the objective function is maximized with the application of 6 fuel management interventions. When the timber owner is liable for all costs including $D$, the harvest date is 43.7 years; expected suppression is 87.2 units, and the value of private and social net benefit is $9,223. Intervals between fuel interventions are shorter when the timber owner is liable for all potential damage. For case 1 with landowner liable for $D$, the expected time of a wildfire given the optimal intervention dates is $E[x] = 42.8 < T_7$. 
For case 1 given that the owner is not responsible for non-timber losses $D$, the harvest date is later 45.0 years. The probability of reaching harvest without a wildfire in this case is $S(T_5)=0.93$, whereas the probability of reaching $t=45$ without fuel treatments is 0.81. Expected suppression effort of 6.13 is substantially lower because we are assuming private suppression effort for this case. Thus, as would be expected, when $D$ is not accounted for privately, fuel management is delayed and suppression effort is reduced. Further, the timber owner’s net benefit is higher than ($9,325) than when $D$ is internalized, but the net social value of the timber rotations is lower.

Figure 1-2 shows the relationship between the number of fuel treatment and optimal suppression effort (with optimal intervention timing conditional the number of treatments) for case 1 without landowner liable for $D$. As the number of treatments increases to $n-1=4$, expected optimal suppression effort decreases. After $n-1=4$, expected suppression effort increases. Two things are happening here: 1) each additional treatment shifts the expected date of a wildfire out, and 2) the optimal harvest date shifts out, leading to larger values at risk because $V(t)$ is growing. Going from $n-1=4$ to $n-1=5$, the (diminishing) marginal value of a treatment in terms of risk reduction is more than offset by the higher marginal value product of suppression due to growth in $V(t)$, so higher suppression expenditures compensates for diminishing returns of fuel treatments.

Case 2 restricts suppression to equal zero and is included in table 1-1 for comparison with case 1. Here, the number and timing of the fuel management interventions and the harvest date are the only means of addressing wildfire risk. Compared to Case 1, fuel management and harvest dates are earlier, and when the timber owner is not liable for $D$, the number of fuel
management interventions is higher by one compared to the case 1 analogue. Thus, earlier fuel treatments (and perhaps more of them), and earlier harvest, act as substitutes for suppression. Note also that both private and social net benefits are lower than in their comparable case 1 results.

In case 3, no fuels management regime is implemented, so suppression and timber harvest timing alone are relied upon as choice variables. Loosely speaking, this case might represent the general approach followed by the U.S. forest service throughout most of the 20th century. Timber harvest dates are 31.9 and 33.3 years when liable and not liable for D, respectively. In each case, timber rotation lengths decrease approximately 8 years compared to case 1. Suppression levels are lower than case 1 (25.6 and 4.7 when liable for D or not, respectively). Thus, most of the effect of ignoring fuel treatments as an option is accounted for by reductions in harvest dates, and given that harvest rotations are short, timber-values at risk are lower at the expected wildfire date, and so the marginal value product function of suppression is lower, so less suppression is used.

Case 4 assumes both fuel management and suppression are restricted to be zero, so the timber harvest date is the only choice variable. As one might expect, harvests dates are the shortest of all cases, occurring at 26.3 and 30.2 years with and without timber-owner liability for non-timber values, respectively.

It is of particular interest to note that of all management regimes so far, those in which fuel management is restricted provide the lowest expected net present value (cases 3 and 4, liable for D both to the forest owner and to society. This result is supportive of the increasingly fervent calls for the importance of fuels management in fire-prone environments.
3.2. Public suppression

Cases 5 and 6 are based on the assumption that in the event of a wildfire, a public agency applies suppression optimally, given private fuel accumulations up until the date of the fire. Therefore, “optimal” suppression in this case is second best in the sense that private fuel management will be inefficient because timber owners are not bearing the suppression component of the costs of wildfire, and will therefore alter their fuel management regimes relative to case 1 (the efficient case).

Case 5 shows the result with publicly provided suppression and private fuel management. The simulation shows that public suppression of 89.6 and 91.9 units (with and without landowner liability for $D$, respectively) is higher than any case in which suppression costs are borne by the timber owner. When the timber owner does not account for non-timber damage, the harvest date of 46.2 years and net private benefit of $9,351 are the highest of all scenarios. The number of fuel interventions is reduced to 2, and the lengths of intervals between them increases.

With public suppression and no fuel management, as in case 6, harvest dates are again shorter, but public suppression is at its highest of all (99.9 and 105.5). Given the assumption that harvest and fuel treatments mitigate fire risk, and regardless of potential non-timber losses internalization, this case provides lower social benefits ($7,604 and $7,570) compared to case 5, where fuel treatments are applied.

Of all the cases presented, these last two scenarios with public suppression and no liability for potential non-timber damage are perhaps the most similar to the incentives of private landowners in most of the United States. Weak incentives to invest in wildfire prevention through fuel management and long harvest rotations lead to very high public suppression
expenditures. These results are consistent with the increasing suppression costs and wildfire severity observed over the past decades. In effect, since fire suppression expenditures are supported almost entirely by public agencies, there is little private incentive to invest in preventive actions such as fuel treatments. This lack of prevention ultimately leads to more catastrophic fires and to increasing public firefighting expenditures.

Although the above simulations provide insights into the trade-offs between suppression and fuel treatments that cover a broad range of wildfire issues, they are based on just one set of underlying physical relationships between timber growth, wildfire risk, fuel management, harvest, costs, and benefits. There are many ways in which the model could be respecified to better fit a given situation. For example, we have applied the same suppression productivity function to timber and non-timber values, but it is likely that approaches to protecting homes are different than approaches to protecting timber, implying that the suppression productivity function would differ. We have also assumed that the timber stumpage value is not a function of the treatments’ timing, when in fact it is likely that thinning and prescribed fire activities also often augment timber growth. Finally, the optimistic assumption of second-best public firefighting effort almost certainly grossly underestimates the level of suppression effort exerted by firefighting agencies.

4. Policy and Management implications

Wildfire fuels and values at risk change over time, so wildfire risk management is in part a timing problem. In this article, we embed the wildfire management problem in a setting that captures many of the important elements affecting incentives for private and public wildfire risk mitigation, and many of the most pressing policy questions as well.
Fuel management provides positive externalities to the extent that it reduces the contribution of a landholding to regional wildfire risk. Although there are good reasons for public provision of wildfire suppression services, one consequence of public firefighting services is that the private marginal costs of waiting to invest in fuel management are not fully internalized by the landowner or forest manager. The result of these two incentive problems is “too little, too late” private fuel management, and public suppression expenditures that are substantially higher than they might otherwise be. A century of this combination of incentives may be a major contributor to the apparent substantial increases in suppression costs and wildfire severity in recent years.

The legal and regulatory environment frames private incentives for fuel management. There are a small but growing number of public programs and laws pertaining to wildfire fuel management that arguably tries to address the incentive problems illustrated in this paper. A few states have cost-share programs for fuel reduction on private land, and laws have been proposed in several state legislatures to direct the funding needs for suppression at forest owners specifically. As these laws develop, it is important that they be designed to affect fuel management choices at the margin for individual forest owners.

One interesting legal conundrum relates to prescribed fire, which is often the least-cost method of wildfire as a fuel management option. Although legal liability for prescribed fire use is relatively clearly established in statutory and common law, legal liability for accumulation of excessive fuel loads is not (Yoder et al., 2003). If a wildfire starts or flows through a

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7On the wildland-urban interface, it is also important to balance the incentives of forest owners with the incentives of homeowners. “Moving to the hazard” and homeowner incentives are an important element of this problem, but because the focus of this paper focuses on timber owners specifically, we leave these issues aside.
landholding, the landowner is usually not at risk of liability for excessive fuel loads. But, if a prescribed fire started for fuel management purposes escapes and turns into a wildfire, the person performing the prescribed fire faces relatively well-developed negligence law (Yoder et al. 2003). Thus, although the full-expected costs of prescribed fire may be approximately accounted for, the costs of leaving the fuel alone may not.

The relationship between wildfire and timber harvest is also a contentious issue. George W. Bush’s precursor to the Healthy Forests Restoration Act of 2003, The Healthy Forest Initiative, discusses fuel management at length, but environmentalists attacked the initiative as a politically motivated attempt to open the door for increased timber harvest. Furthermore, many fire ecologists claim that timber harvest, particularly old growth, is usually not an effective means of reducing wildfire risk. The structure of our model elucidates a couple of dimensions of this issue. First, the type of property at risk matters. If timber values are at risk, it makes sense to harvest earlier in areas with high wildfire risk, preempting wildfire losses by extracting value. For non-timber values, altering timber harvest timing is a form of fuel management for wildfire risk reduction. If timber harvest is ineffective at reducing wildfire risk to non-timber values, then shortening timber harvests makes little economic sense in terms of reducing non-timber losses. On the other hand, if harvest does reduce the risk of non-timber damage, then shorter rotations make economic sense. This last point is illustrated by the harvest

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8A few states do have statutory negligence laws for individuals who do not attempt to stop a fire from spreading from their land.
9In four states, however, landowners or contractors can be found liable for activity fuels such as timber slash, where a specific activity, such as timber harvest, can lead to substantially increased wildfire risk. The characteristic of being able to pinpoint a specific action (e.g. the creation of timber slash) is helpful for clearly assigning liability and negligence through the courts; at the margin, it is likely more difficult to pinpoint a threshold of negligence with respect to natural fuel accumulation.
10In simulations examined in this article we assume that both harvest and wildfire interventions reduce wildfire risk to zero, but the model can easily be specified to differentiate between the two activities and allow for incomplete risk reduction in either case.
date differences between the scenarios in which the timber owner is responsible for non-timber values and those in which the timber owner is not responsible for non-timber values.

As is the case with much of the recent wildfire management literature, the emphasis of the Healthy Forests Restoration Act of 2003 is on the spatial distribution of wildfire risk mitigation, with explicit directives to focus spatially on the wildland-urban interface. Nonetheless, the fuel management is a dynamic temporal problem as well. Although the model presented in this paper is modeled as a single fire-prone forest stand, a useful further development would be to incorporate the dynamic model into a broader spatially explicit model of wildfire risk management.
Table 1-1: Simulation Results: Cases 1-4: Private owners bear the costs of suppression. Cases 4-6: Suppression provided by a public agency.

<table>
<thead>
<tr>
<th>Management Strategies</th>
<th>Owner responsible for $D$</th>
<th>Fuel treatments $(n-1)$</th>
<th>Harvest Dates</th>
<th>Suppression Date</th>
<th>Net Private Benefit</th>
<th>Net Social Benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1: Private suppression and fuel treatments</td>
<td>Yes</td>
<td>13.7</td>
<td>21.0</td>
<td>26.8</td>
<td>32.2</td>
<td>37.0</td>
</tr>
<tr>
<td>Case 1: No</td>
<td>No</td>
<td>6</td>
<td>41.2</td>
<td>43.7</td>
<td>87.2</td>
<td>9,223</td>
</tr>
<tr>
<td>Case 2: Fuel treatments only</td>
<td>Yes</td>
<td>13.1</td>
<td>19.9</td>
<td>25.7</td>
<td>31.3</td>
<td>35.7</td>
</tr>
<tr>
<td>Case 2: No</td>
<td>No</td>
<td>4</td>
<td>42.7</td>
<td>45.0</td>
<td>6.13</td>
<td>9,325</td>
</tr>
<tr>
<td>Case 3: Private suppression only</td>
<td>Yes</td>
<td>31.9</td>
<td>26.6</td>
<td>9,239</td>
<td>7,290</td>
<td></td>
</tr>
<tr>
<td>Case 4: No suppression or treatments</td>
<td>No</td>
<td>33.3</td>
<td>4.7</td>
<td>7,711</td>
<td>7,711</td>
<td></td>
</tr>
<tr>
<td>Case 5: Public suppression and private treatments</td>
<td>Yes</td>
<td>26.3</td>
<td>7,808</td>
<td>7,418</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 5: No</td>
<td>No</td>
<td>16.2</td>
<td>30.2</td>
<td>3,228</td>
<td>3,228</td>
<td></td>
</tr>
<tr>
<td>Case 6: Public suppression only</td>
<td>Yes</td>
<td>16.2</td>
<td>30.2</td>
<td>6,936</td>
<td>2,472</td>
<td></td>
</tr>
<tr>
<td>Case 6: No</td>
<td>No</td>
<td>4</td>
<td>41.8</td>
<td>45.1</td>
<td>9.211</td>
<td>8,750</td>
</tr>
</tbody>
</table>

**Private**
Figure 1-1: Wildfire probability distributions, with fuel management interventions (solid lines) and without interventions (dotted lines). Interventions are shown to be applied at increasing frequency as is optional when timber value grows over time.
Figure 1-2: Substitution between the number of (conditionally optimal) fuel interventions and the amount of suppression effort. Case 1 (landowner not liable for $D$; optimal number of treatments $= 4$).
References


CHAPTER II
AN ECONOMETRIC MODEL OF WILDFIRE SUPPRESSION PRODUCTIVITY

1- Introduction

Wildfire suppression expenditures have been rising by all accounts over the past decade (Ingalsbee, 2000, O’toole 2002). Since 1990, fire seasons have been more expensive than the initial suppression appropriations and have required emergency funding almost every year (GAO, 2004).

Wildfire suppression is an attempt to reduce damage imposed by wildfires. Economic models have been around since the 1920’s that focus on minimizing the sum of suppression costs and wildfire damage (Sparhawk 1925). Donovan and Rideout (2003) summarize this history and develop a generalization of the cost plus loss framework, more recently termed “cost plus net value change,” henceforth C+NVC, where C represents all the costs associated with suppression activities and NVC denotes net loss in resource value from wildfire. Since its introduction, the model has been extensively used in theoretical work on wildfire cost minimization and in public wildfire management decisions making.

The foundation of the cost plus loss framework is a suppression productivity function that relates suppression effort to reduction in wildfire damage. Despite the widespread conceptual use of the C+NVC model, to our knowledge, no one has successfully estimated a suppression production function in any setting, and thus no empirical basis for the C+NVC model exists for any setting.

This paper provides an empirical basis for the cost plus loss model of fire suppression, and investigates the economic returns from investments in suppression activities. Using national
level data for individual wildfires, we estimate a model of suppression productivity, where suppression productivity is measured in terms of the reduction in the estimated market value of wildfire losses in response to suppression effort. We posit that suppression effort and a target acreage (or containment area) are choice variables in the process of reducing damage from wildfires. We develop a structural model in which suppression effort, acreage burned, and resource damage are simultaneous determined within a system of regression equations. The analysis is conducted using the National Interagency Fire Management Integrated Database (NIFMID) data and supporting data from other sources.

As expected, our results show that an increase in suppression expenditures reduces resources damage. However, our analysis shows that returns from investment in suppression at the margin are small compared to the suppression investment, suggesting an over-allocation of funding to suppression activities. We also find that pre-suppression activities (preparedness, in particular) provide substantial economic returns at the margin. Taken together, these results suggest that limited funding should be directed away from suppression and toward pre-suppression.

The rest of the paper is organized as follows. In section 2, we present a reformulation of the cost plus loss model of fire suppression that provides a foundation for our empirical analysis. Section 3 presents the estimable model. In section 4, a description of the data is provided. The estimation approach and results are discussed in sections 5 and 6 respectively, and in section 7 we discuss policy implications and provide concluding remarks.

2- Theory

The C+NVC model has been central to theoretical discussions about minimizing wildfire
costs for most of this century.\textsuperscript{11} It represents the net sum of all wildfire related costs, where $C$ denotes all costs associated with fire suppression, and $NVC$ denotes net fire related damages (see figure 2-1). The objective in the $C+NVC$ model is to minimize the sum of fire management expenditures plus the net change in resource values due to wildfire (González-Cabán et al 1986, Hesseln and Rideout 1999), where expenditures on fire suppression ($C$) are intended to reduce net fire-related damages (Donovan and Rideout 2003). The theoretical framework of this paper builds on the Donovan and Rideout (2003) version of the $C+NVC$, but extends it to allow for endogenous and exogenous interactions between suppression expenditures, resource damage and total acreage burned for each fire.

For notational convenience, assume that $NVC$ is always non-positive, and that $NVC=d$ where $d$ defines resource damage value. The total cost of a fire is the sum of suppression costs and damage. Total cost for a given fire is minimized by jointly choosing the target acreage (the wildfire containment area) and suppression effort. We hypothesize that although increasing the size of the containment area will likely increase the amount of resource damage from the fire, it can reduce the marginal costs of suppression for a given containment area.

The hypothesized ex-post cost function, representing the costs of a fire after the fire is dead out, is specified as:

$$c + d = \varepsilon, w(\varepsilon, a; Z_s) s + \varepsilon, d(\varepsilon, a, s; Z_d)$$  \hspace{1cm} (1)

Where

- $(c + d)$ is cost plus damage
- $\varepsilon, s \sim (1, \sigma^2_s)$ is a random disturbance to suppression costs with unit mean. As

\textsuperscript{11} See Headley 1916, Sparhawk, 1925, Simard 1976, Blattenberger and others 1984, González-Cabán and others 1986, Hesseln and Rideout 1999
modeled, it can be thought of as either a random disturbance to the marginal cost, or a random disturbance to suppression effort, or both.

- $w$ is the marginal cost of suppression, which is dependent on a vector of variables $Z_s$ that includes pre-suppression inputs applicable for a particular fire, and other determinants of marginal suppression costs.

- $a$ is the chosen target acreage (containment area) for suppression efforts. The actual ex-post fire acreage is $a + \varepsilon$, where $\varepsilon$ is a random variable with mean and variance $\varepsilon \sim (1, \sigma^2)$.

- $s$ is suppression effort, a choice variable.

- $d$ is damage from a fire, and it is a function of the actual acreage, suppression effort $s$, and other factors $Z_d$. The error term is distributed $\varepsilon \sim (1, \sigma^2)$.

Assume that at the margin, allowing a larger containment area is expected ex ante to reduce the marginal cost of suppression, so that $\frac{\partial w}{\partial a} < 0$, but that increased acreage increases damage, so that $\frac{\partial d}{\partial a} > 0$. Suppression effort is exerted to contain the fire within the containment area, and it may also reduce damage for a given number of acres, so that $\frac{\partial d}{\partial s} < 0$.

Assume that cost minimization decisions are completed prior to the fire being extinguished and that the optimal policy is to minimize expected cost plus net value change. Given that all disturbances are uncorrelated and enter the $c+d$ function multiplicatively, the ex ante expected total costs plus net value change of a fire based on a target acreage, suppression effort is then:

$$E[c + d] = w(a; Z_s)s + d(a, s; Z_d)$$  \hspace{1cm} (2)
Assuming that the second-order conditions for a maximum hold, the first-order conditions to maximize $E[c+d]$ are:

$$\frac{\partial E[c+d]}{\partial s} = w + \frac{\partial d}{\partial s} = 0,$$

Or

$$w = -\frac{\partial d}{\partial s} \tag{3}$$

$$\frac{\partial E[c+d]}{\partial a} = \frac{\partial w}{\partial a} s + \left( \frac{\partial d}{\partial s} \frac{\partial s}{\partial a} \right) = 0$$

$$= \frac{\partial w}{\partial a} s + w \frac{\partial s}{\partial a} = 0. \tag{4}$$

The first order condition with respect to suppression costs can be obtained by directly deriving objective function [2] with respect to suppression cost value ($w$ $s$). Specifically:

$$\frac{\partial E[c+d]}{\partial (ws)} = 1 + \frac{\partial d}{\partial (ws)} = 0$$

Or

$$\frac{\partial d}{\partial (ws)} = -1 \tag{5}$$

Which implies that if suppression is being applied at an efficient level, one dollar invested in suppression costs reduces wildfire damage by one dollar. Given diminishing returns to suppression, $\frac{\partial d}{\partial (ws)} < -1$ means that one dollar of suppression reduces damage by more than one dollar at the margin and implies too little suppression; $\frac{\partial d}{\partial (ws)} > -1$ means that one dollar of suppression reduces damage by less than one dollar at the margin and implies too much suppression effort.

The *ex ante* derived demands for suppression and acreage are then

$$s^* = s(Z_s, Z_d) \tag{6}$$
\[ a^* = a(Z_s, Z_d) \]  

We do not have data for \( s^* \), the actual suppression effort. However, we do have data for \textit{ex post} suppression costs, acreage, and damage, which are defined in our model as:

\[ a^o = \varepsilon_a a(Z_s, Z_d) \]

\[ = \varepsilon_a a^* \]  

\[ c^o = \varepsilon_c w(\varepsilon_a a^*; Z_s) s^* \]

\[ = \varepsilon_c w(a^o; Z_s) s^* \]  

\[ d^o = \varepsilon_d d(\varepsilon_a a^*, s^*; Z_d) \]

\[ = \varepsilon_d d(a^o, (c^o / \varepsilon_c w(a^o; Z_s)); Z_d), \]  

where \( c^o / \varepsilon_c w(\varepsilon_a a^*; Z_s) \equiv s^* \) in equation [11] is derived by solving equation (9) for \( s^* \) and substituting the right hand side into equation [10].

Actual acreage \( a^o \) (rather than the containment area \( a^* \)) is included as an argument for the average marginal cost of suppression. In this model, the difference between the two represents the additional acreage resulting when a wildfire escapes the containment area. The actual acreage is included in equations [9] and [10] because \textit{ex post} escapes may affect the marginal costs of suppression. However, whether \( a^o \) or \( a^* \) should be included as explanatory variable in the damage equation is an empirical question that is addressed with an endogeneity test for \( a^o \).

Equations 8, 9, and 11 are the general form for estimable equations for \( c^0 \), \( a^0 \), and \( d^o \). Specific functional forms must be chosen for estimation, which we discuss next.
3. Functional forms for estimation

Preliminary regressions suggest that the underlying disturbances \( \varepsilon_a \) and \( \varepsilon_s \) approximate censored lognormal distributions. Censoring issues will be addressed later. To allow linear-in-parameters estimation, we utilize generalized Cobb-Douglas functional forms.

For notational ease, let \( \mathbf{Z} = [\mathbf{Z}_a \ \mathbf{Z}_s \ \mathbf{Z}_d] \), which contains all available exogenous variables, and let \( \mathbf{Z}^{\beta_j} = \prod_{i=1}^{k} Z_i^{\beta_i} \) represent the Cobb-Douglas functional form for the \( j \)th equation.

First, we specify observed acreage defined in equation (8) as:

\[
\alpha^o = e^{\alpha_a} \mathbf{Z}^{\beta_a} \varepsilon_a
\]

so that the log-linear estimable equation is

\[
\ln \alpha^o = \alpha_a + \beta_a \ln \mathbf{Z} + u_a
\]

where \( u_a = \ln \varepsilon_a \sim N(0, \sigma_a^2) \).

To specify \( c^o \) (equation 9), the functional form of the (unobserved) marginal cost of suppression effort must be specified. Let

\[
w(\alpha^o; \mathbf{Z}_s) = e^{\alpha_w} \mathbf{Z}^{\beta_w} (\alpha^o)^{\delta_s}, \text{ or } \]

\[
e^{\alpha_w} \mathbf{Z}^{\beta_w} e^{\alpha_s} \mathbf{Z}^{\beta_s} \varepsilon_a
\]

\[
e^{\alpha_s} \mathbf{Z}^{\beta_s} \varepsilon_a
\]

where \( \alpha_w = \alpha_w + \alpha_a \) and \( \beta_w = \beta_w + \beta_a \).

Unobserved suppression effort is

\[
s^* = e^{\alpha_s} \mathbf{Z}^{\beta_s}.
\]

Putting the marginal cost and effort functions together, the suppression cost function (equation 9)
then becomes
\[
c^* = \varepsilon_s w (a^*; Z_s) s^*
\]
\[
= e^{\varepsilon_s w_1 (a^*)^\delta} e^{\varepsilon_s Z^\beta \varepsilon_s E_s}
\]
\[
= e^{\varepsilon_s (a^*)^\delta} Z^\beta \varepsilon_s E_s
\]
(16)
where \( \alpha_c = \alpha_w + \alpha_s \), \( \beta_c = \beta_w + \beta_s \), \( \delta_c = \delta_w \). Taking natural logs of both sides of equation [16] provides
\[
\ln c^* = \alpha_c + \delta_c \ln a^* + \beta_c \ln Z + \varepsilon_c
\]
(17)
where \( \varepsilon_c = \ln \varepsilon_s e_s \) has mean zero and is correlated with \( u_a \).

The damage function [10] is specified as:
\[
d^* = e^{\varepsilon_d w_2 (a^*)^\delta_1 (c^*/\varepsilon_s w(...)^\delta_2 Z_d^\beta \varepsilon_d}
\]
\[
= e^{\varepsilon_d (a^*)^\delta_1 (c^*)^\delta_2 (e^{a^* Z^\beta \varepsilon_s})^{-\delta_2} Z^\beta \varepsilon_s^{-\delta_2} \varepsilon_d}
\]
\[
= e^{\varepsilon_d (a^*)^\delta_1 (c^*)^\delta_2 Z_d^\beta \varepsilon_{d1}}
\]
(18)
(19)
where \( \alpha_d = \alpha_{d1} + \alpha_w \), \( \beta_d = \beta_{d1} + \beta_w \), \( \beta_d = \beta_{d1} + \beta_w \), and \( \varepsilon_{d1} = \varepsilon_s^{-\delta_2} \varepsilon_d \).

Again, whether to include the original observed suppression cost and/or acreage rather than the estimated planned acreage and suppression costs \( c^* \) and \( a^* \) can be determined by an exogeneity test.\(^{12}\) If testing shows that \( a_o \) and/or \( c_o \) are correlated with \( \varepsilon_{d1} \), these two variables can be replaced with estimated values of \( a^* \) and \( c^* \).

The log linear form of equation [19] is then
\[
\ln d^* = \alpha_d + \delta_{d1} \ln a^* + \delta_{d2} \ln c^* + \beta_d Z_d + u_d
\]
(20)

\(^{12}\)The model suggests that the observed values of these variables should be uncorrelated with the disturbances, but in practice they may be due to measurement error or omitted variables.
where \( u_d = \ln \epsilon_s^{\delta_1} \epsilon_{d1} \sim N(0, \sigma^2) \). Given the interpretation of \( a^o/a^* = \epsilon_a \) as relating to acreage beyond the planned containment area, endogeneity of \( a^o \) in equations [15] and [20] suggests that \( \epsilon_a \) is correlated with costs and damage with escapes. Further, because \( \epsilon_s \) is an element of \( \epsilon_{d1} \), the disturbances of the cost and damage equations are correlated. Thus, there will likely be correlation among the disturbance terms in all-estimable equations because they are related through the two underlying disturbances \( \epsilon_a \) and \( \epsilon_s \). This correlation will be accounted for to improve the efficiency of our estimators.

4-Data

The data used in this project were a compilation of a variety of data dating from 1970 to 2002, and covering the continental United States. A map showing location and distribution of the wildfires occurring in the US for the period 1970-2002 is shown in figure 2-2.

Fire and fire expenditure data were collected from two sources: the National Interagency Fire Center (NIFC), and the National Fire and Aviation Management (FAMWEB), which supports both the Kansas City Fire Access Software (KCFAST), and the National Interagency Fire Management Integrated Database system (NIFMID). These data were concatenated based on a unique fire identification number. All fire expenditure data (estimated fire pre-suppression and suppression cost), and fire damage data were deflated using the Consumer Price Index (CPI, base year 2000) collected from the USDL Bureau of Labor Statistics. Table 2-1 provides a summary statistics of the data.

Donoghue (1982) reviews the history of wildfire data reporting and provides an
assessment of the Forest Service fire data. Fire report forms are filled out by fire managers and a number of factors might contribute to inaccuracies. For instance, time lag between the occurrence of a fire and its documentation may result in imperfect recollection and therefore imperfect data. Also, when facing several quickly spreading fires, managers “attention to [data] details and accuracy might be sacrificed as efforts to save time” (Donoghue, 1982). In our analysis, some of the variables used, such as resource damage, are difficult to observe and may be vaguely defined, leading to variation across individual reports.

The first wildfire report form was issued in 1905, and it has been changed in various ways between then and now. The beginning of our sample in 1970 coincides with a major re-issuance of the report form. There are some relatively minor differences between the form in 1970 and the form used in 2002, but a systematic accounting of these changes (and the timing of these changes) after Donoghue’s 1982 paper appears not to be available. However, based on visual examination of the data used in this analysis, there appear to be some substantial structural changes between 1970 and 2002 for some variables. For some variables there are significant numbers of missing observations, a number of variables have apparent structural changes in reporting.

In addition to factors that appear to stem from inaccuracies, omissions, and changes in reporting is another complication for estimation because all three dependent variables are censored at or near zero for a substantial percentage of observations. In the next two sections, we present the variables and discuss how the data limitations were addressed.
4.1 Endogenous variables

There are a number of characteristics and limitations associated with each of the dependent variables that must be addressed. We first discuss resource damage data \( (d^o) \), then suppression costs \( (c^o) \) and area burned \( (a^o) \). We also discuss the relationships between these variables.

For the years 1985 to 1994 resource damage \( (d^o) \) values observed appear systematically different than the surrounding years (figure 2-3). Many zeros or very small damage values are reported for this period. This discrepancy is confirmed by comparing figure 2-4 with acreage burned and suppression costs figures for the same period (figures 2-6 & 2-9). We see for instance that two of the top ten total acres burned years fall within the same interval (1985-1994) in which resource damage values are relatively very small. To address these apparent reporting differences while making full use of the dataset, we account for these large shifts by using dummy variables corresponding to these structural shifts, and/or run regressions based on sub-samples of data.

Another problem of resource damage data related to the previous one is the large amount of zeros (55.3%) and missing observations (31.1%). The high percentage of zero characterizes a censoring problem, which must be dealt with econometrically in order to estimate model parameters consistently (Maddala, 1999, chap 6). Figures 2.4-2.5 represent the log-transformed distributions of these data respectively with and without the censored observations. We account for the censoring issue by using a Tobit model specification for our estimation and run regressions that either omit observations with missing damage data, or code the missing damage data as taking the value of zero, assuming that managers may be likely to omit a value of their estimate of damage is approximately zero.
The definition of damage in the NIFMID data is relatively vague. The “value of resources damaged or destroyed” includes timber values and non-timber values, including damage to “watershed”, “recreation”, “range and wildlife”, “improvements”, and “other non-timber.” Estimates of non-timber damage values as listed are likely to be very rough due to the difficulty of estimating these characteristics. More recently, estimating the net value change from a wildfire entails the use of additional calculation tables (and usually computer modeling) based on land characteristics and standardized unit values to assess net value change (National Interagency Fire Center 2000, Schuster and Krebs 1999).

Estimated Forest Service suppression cost \( (c^e) \) accounts for the costs of suppression equipment (such as airplanes, helicopters and water tenders) and services (such as line crew labor and overhead management) to suppress forest fires (Schuster and others 1997). In principle, these costs are estimated for each individual fire and entered into the NIFMID database. However, because deployment of equipment and personnel in some cases corresponds to suppression of more than one wildfire, disaggregation of cost data may in some cases be imperfect. Only the Forest Service related expenditures are included, while expenditures of other agencies are not accounted for (Schuster and others 1997). However, the US Forest service is the agency most involved in wildfire suppression, and it is usually the primary actor in most wildfire suppression actions.

Schuster (1999) examines Forest Service Wildland Fire Management Expenditures and develops aggregate estimates of wildfire expenditures. His data sources include the original

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13 The ability to assess these non-market wildfire related damage has been a topic of research conducted by Rideout and others (1999) and Loomis et al. (1999), among others.
sources from which the NIFMID data come. In figure 2-6, we observe a low plateau in aggregate annual suppression costs from our dataset for the years 1983-1988, which correspond to the years that Schuster found a substantial amount of missing records. Figure 2-6 shows a large shift in the cost pattern in 1987, reflecting change in suppression and pre-suppression expenditure data collection and reporting, also described by Schuster (1999). We account for these effects by using dummy variables in the estimation. Among other data collection and reporting discrepancies, Schuster (1999) finds that some expenditures where labeled pre-suppression when in fact the expenditures where used for the suppression of wildfire.

It should be noted that although there are undoubtedly missing records in the dataset that we are using that will reduce the estimated aggregate expenditure estimates, our analysis is based on individual fire level data. Given the discussion by Schuster (1999), there may be some degree of sample selectivity across forest service regions, but the potential extent of potential selection is unclear. Although we do not address potential selectivity explicitly (partly due to data limitations), we do address regional differences in our analysis as discussed later. The suppression cost data exhibit substantial censoring, with 18.1% of the observations taking value zero. Figures 2.7-2.8 provide aggregate illustrations of the cost data by year, as well as histograms based on the natural logs of cost, with and without the censored data. Censoring will be addressed in model estimation.

The final endogenous variable is total wildfire acreage \( (a') \). Figure 2-9 shows a large shift in pattern in year 1987, again corresponding to data reporting changes discussed in Schuster (1999). We again account for this reporting shift using dummy variables in the estimation. As with resource damage and suppression costs, censoring of acreage is an issue to be addressed in
estimation. Sixty one percent of acreage observations take the value 0.1 (one-tenth of an acre is the lowest reported value for wildfires). In figures 2.10-2.11 we represent the log-transformed distribution for these observations with and without the censored values.

Figures 2.12-2.14 show the relationships between resource damage, fire expenditures and area burned. A scatter plot of resource damage against suppression expenditures (figure 2-12) suggests a positive relationship, which seems to imply that fire suppression activities are related to higher damage levels. Indeed, a simple ordinary least squares regression of \( \ln(d) \) on \( \ln(s) \) would suggest that suppression expenditures “cause” higher damage. Given that the purpose of suppression is to reduce damage, this result makes no sense. The key to this conundrum is that while suppression effort (as measured by expenditures here) surely tends to reduce resource damage, it is also the case that suppression efforts tend to be higher for larger, more damaging fires. This is to say that for a given fire, suppression costs and damage are jointly determined (endogenous). Because wildfire suppression entails choosing containment areas, this is true of wildfire acreage as well. Our estimation approach to deal with censoring and endogeneity will be discussed later.

4.2 Explanatory variables

To estimate suppression cost, wildfire damage and acreage, we use variables such as topographic information, weather, and population density, all of which constitute the vectors \( Z_j \) \((j=a, c, d)\) of exogenous variables introduced previously. Below, we describe these variables.

Slope (SLOPE) is included as an explanatory variable in the model regressions because of the significance that it plays in fire behavior and total fuel consumption. Slope also plays a
crucial role for fire personnel and equipment as steeper slopes make fires more difficult to reach for suppression effort. For this reason the sign of slope is expected to be positive in the acreage, suppression cost, and resource damage equations.

Elevation (ELEV) is another landscape characteristic included in the regression to capture the effect of both differences in vegetation types across elevation zones, and as a proxy to capture differences in the difficulty of fighting wildfires at different elevations.

The aspect variables AN, AS are composite dummy variables representing North and South facing slopes respectively. Aspect will influence the amount of damage caused by a fire due to the amount and type of vegetation found on each respective aspect, as well as differences in sunlight, heat, and fuel moisture content.

The average cumulative precipitation for the year beginning January 1 (PRCP) is included in the damage and costs regressions to capture the effects that cumulative rainfall and moisture have on fuel load growth in spring and fuel moisture content at the time of the fire.

Maximum temperature (TMAX) is a daily state average maximum temperature on the day of fire ignition for the state in which the fire occurred. Maximum temperature is included in damage and suppression cost regressions because temperature during the fire will affect the intensity and rate of spread of a fire.

The Palmer Drought severity index (PDSI) (Palmer, 1965) uses temperature and rainfall information to determine dryness (NOAA). The index generally varies between -6.0 and +6.0 where the lowest limit represents extremely dry spells and the upper limit indicates extreme wet spells. We collected statewide monthly observations for this variable and computed average

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14 Variable ASPECT was coded with three dummy variables (Aspect north (AN), Aspect south (AS), Aspect flat (AF). The dummy AF was dropped to avoid the dummy trap; the intercept therefore corresponds to this category.
annual and lagged values. Both variables \(\text{PDSI} \text{ and } \text{PDSI}_{\text{lag}}\)\(^{15}\) are included in the acreage regression to explain fire severity. Drought index for concurrent years are expected to have a negative effect on fire severity, while drought index of the preceding year are expected to affect fire severity positively (Swetnam and Betancourt, 1998).

Delay \((DL)\) is used in the regression to account for the time difference between ignition and discovery date of a fire. The lag in time between ignition and discovery will influence how much damage is caused by wildfire. The larger the time lag, the more likely that the fire spreads into a larger one, causing greater damage. The sign of the coefficient \(DL\) is expected be positive in all three equations. A squared term of the time response to a discovered fire \((DL_{sq})\) is included to capture possible quadratic effects on suppression costs.

Pre-suppression costs \((PRESUP)\) describe preparedness activities and expenditures occurring prior to a fire (e.g. planning, prevention, detection and equipment and supply purchases, salaries, etc). Pre-suppression costs data are available annually by Forest Service region. We computed and used in regressions the average pre-suppression cost for individual fire events for a given region and year, so that the pre-suppression value for a given fire represents the average preparedness expenditure in that forest service region an year in which the fire occurred. The pre-suppression data are not part of the NIFMID dataset, and were acquired from the National Interagency Fire Center.\(^{16}\)

Fire Intensity Level \((FILhat)\) is included in the model because it is an estimate of fire behavior. High fire intensity levels are expected to cause more damage. Approximately 52% of

\(^{15}\) We rescaled the average annual PDSI (=PDSI+10) in order to consider the logarithm

\(^{16}\) Another element of the pre-suppression data corresponds to expenditures on fuel management by region and year. Because the specific location of these activities could not be matched to specific wildfire sites within a region, this component of the pre-suppression data were not useable.
the observations for this variable were missing from the dataset. Using information on other variables available in the data (temperature, precipitation, slope, elevation), and assuming a linear relationship between these regressors and the fire intensity level variable, we estimated the missing values based on OLS regression (see Greene, 2000, p.259).

Population density ($POPden$) is believed to influence decision-making regarding suppression expenditures. Wildfires in areas with high population densities will more likely draw more suppression effort than a similar fire in less populated areas. Because wildfire locations are coded either by latitude, longitude or by township, and range, we matched these locations data with county FIPS codes using ARC/INFO and TRS2LL software. County population density was then merged with the wildfire dataset based on FIPS codes. We expect that higher population density would affect suppression cost positively presumably because more resources will be allocated to protect life and property. Thus population density is a proxy for values at risk in the region of the fire.

Year dummy variables are introduced respectively in area burned and suppression costs regression ($Year87$), and in the resource damage regression ($YearD$), to capture the apparent changes in data collection patterns. We take into account regional specificities by introducing a dummy variable for each Forest Service region ($R_i$ where $i = 1, ..., 9$).

Summary statistics and a descriptive summary of variables used in estimation are provided in Tables 2-1 and 2-2.

5- Estimation approach

From our previous discussion, two main econometric issues, endogeneity and censoring, must be taken into consideration in specifying our empirical model, which includes three
interrelated regression equations (one each for suppression costs, containment acreage, and damage). We specify a simultaneous Tobit system with endogenous regressors, where the error term for each equation is censored normally distributed. We estimate the model using a three-stage minimum distance estimator developed by Muthén (1984), and Muthén et al (1997).

5.1- Econometric model

Let \( l_a \) be the censoring limits for dependent variable acreage ln \( a \). Equation [13] is specified as:

\[
\ln a^* = \alpha_a + \beta_a \ln Z_a + u_a
\]

\[
\ln a = \begin{cases} 
\ln a^* & \text{if } \ln a^* > l_a \\
 l_a = \ln (0.1) & \text{otherwise}
\end{cases}
\] (21)

Where \( u_a \) is censored normal with mean zero and variance \( \sigma_a^2 \), \( \alpha_a \) and \( \beta_a \) are the coefficients to be estimated, and \( Z_a \) is the vector of exogenous variables.

Similarly, we denote \( l_c \) the censoring point for suppression expenditures. The econometric specification for equation [16] is therefore:

\[
\ln c^* = \alpha_c + \delta_c \ln a^* + \beta_c \ln Z_c + u_c
\]

\[
\ln c = \begin{cases} 
\ln c^* & \text{if } \ln c^* > l_c \\
 l_c = \ln (0.0001) & \text{otherwise}
\end{cases}
\] (22)

Where \( u_c \) is censored normal with mean zero and variance \( \sigma_c^2 \), \( \alpha_c \) and \( \delta_c \) are the coefficients to be estimated, and \( Z_c \) is the vector of exogenous variables.\(^{17}\)

Finally, we let \( l_d \), be the lower limit for resource damage. Equation [20] is thus specified as:

\(^{17}\) In order to calculate the log transformation of \( c^* \) (and \( d^* \) below), zeros were set to 0.0001.
\[
\ln d^o = \alpha_d + \delta_{d1} \ln a^o + \delta_{d2} \ln c^o + \beta_d \ln Z_d + u_d
\]

\[
\ln d = \begin{cases} 
\ln d^o & \text{if } \ln d^o > l_d \\
l_d = \ln (0.0001) & \text{otherwise} 
\end{cases}
\]

(23)

Where \( u_d \) is censored normal with mean zero and variance \( \sigma_d^2 \); \( \delta_d \) and \( \beta_d \) are the coefficients to be estimated, and \( Z_d \) is the vector of exogenous variables affecting resource damage.

The errors terms \((u_a, u_c, u_d)\) are trivariate normally distributed \( \phi(.) \sim N(0, \Psi) \) and assumed identically distributed across observations, where covariance matrix:

\[
\Psi = \begin{bmatrix}
\sigma_a^2 & \rho_{a\sigma} & \rho_{a\sigma_c} \\
\rho_{a\sigma} & \sigma_c^2 & \rho_{c\sigma_d} \\
\rho_{a\sigma_c} & \rho_{c\sigma_d} & \sigma_d^2
\end{bmatrix}
\]

The structural model [20-22] is:

\[
\begin{align*}
\ln a &= \alpha_a + \beta_a \ln Z_a + u_a \\
\ln c &= \alpha_c + \beta_c \ln Z_c + u_c \\
\ln d &= \alpha_d + \delta_{d1} \ln a^o + \delta_{d2} \ln c^o + \beta_d \ln Z_d + u_d
\end{align*}
\]

Given \( k = a, c, d \), this can also be written as:

\[
\begin{bmatrix}
1 & 0 & 0 \\
-\delta_c & 1 & 0 \\
-\delta_a & -\delta_c & 1
\end{bmatrix}
\begin{bmatrix}
\ln a \\
\ln c \\
\ln d
\end{bmatrix}
= \begin{bmatrix}
\alpha_a & \beta_a \\
\alpha_c & \beta_c \\
\alpha_d & \beta_d
\end{bmatrix}
\begin{bmatrix}
1 \\
\ln Z_k
\end{bmatrix}
+ \begin{bmatrix}
u_a \\
u_c \\
u_d
\end{bmatrix}
\]

(24)

Or

\[
\Gamma \begin{bmatrix}
\ln a \\
\ln c \\
\ln d
\end{bmatrix} = \begin{bmatrix}
B_a \\
B_c \\
B_d
\end{bmatrix} \ln Z + \begin{bmatrix}
u_a \\
u_c \\
u_d
\end{bmatrix}
\]

The structural parameters to estimate are \( q = (\Gamma, B_a, B_c, B_d, \Psi) \) where \( \Gamma \) is the (3 x 3) matrix of
the dependent variables coefficients defined above. \( \mathbf{B}_a = [\alpha_a, \beta_a] \) is a \((1 \times k)\) vector of the exogenous variables coefficients for dependent variable acreage. Similarly, \( \mathbf{B}_c = [\alpha_c, \beta_c]; \mathbf{B}_d = [\alpha_d, \beta_d] \) represent vectors of exogenous variables coefficients for suppression cost and damage. \( \Psi \) is the variance-covariance matrix as defined previously.

Dividing both sides of system (23) by \( \Gamma \), the reduced form of the system is derived as:

\[
\begin{align*}
\ln a &= \Gamma^{-1} \mathbf{B}_a \ln Z + \Gamma^{-1} \mu_a \\
&= \Pi_x(q) \ln Z + \nu_a \\
\ln c &= \Gamma^{-1} \mathbf{B}_c \ln Z + \Gamma^{-1} \mu_c \\
&= \Pi_x(q) \ln Z + \nu_c \\
\ln d &= \Gamma^{-1} \mathbf{B}_d \ln Z + \Gamma^{-1} \mu_d \\
&= \Pi_x(q) \ln Z + \nu_d
\end{align*}
\]

(25)

Where \( \nu_i \sim N(0, \Sigma(q)) \) and \( \Sigma(q) = \Gamma^{-1} \Psi \Gamma \) (26)

The reduced system [25] contains 3 equations with all 3 dependent variables subject to censoring. To derive the likelihood function for estimating the vector \( q \), one needs to account for the different domains of integration of the density function \( \phi(\cdot) \). Sickles et al (1978) explain that for a system of \( G \) equations with \( S \) variables subject to truncation or censoring, there are \( 2^S \) sub-samples to consider in order constructing the likelihood function. In our model, 8 sub-samples are therefore accounted for.

First we consider the case of an observation with all dependent variables censored, that is \( \ln a = l_a, \ln c = l_c, \ln d = l_d \). Such observation contributes a function \( L_1 \) to the total log-likelihood function such that
\[ L_1 = P(\ln a = l_a) \times P(\ln c = l_c) \times P(\ln d = l_d) \]
\[ = P(\nu_a < -\Pi_a(q) \ln Z) \times P(\nu_c < -\Pi_c(q) \ln Z) \times P(\nu_d < -\Pi_d(q) \ln Z) \]
\[ = \int_{-\infty}^{-\Pi_a(q) \ln Z} \int_{-\infty}^{-\Pi_c(q) \ln Z} \int_{-\infty}^{-\Pi_d(q) \ln Z} \phi(\nu_a, \nu_c, \nu_d) d\nu_a d\nu_c d\nu_d \]

Similarly, when only one of the dependent variables is censored, and the others take values greater than their censoring point, the contributions are the following univariate conditional log-likelihoods functions:

\[ L_2 = \int_{-\infty}^{-\Pi_a(q) \ln Z} \phi(\nu_a, \ln c - \Pi_a(q) \ln Z, \ln d - \Pi_d(q) \ln Z) d\nu_a \quad \text{for} \quad \ln a = l_a, \ln c = \ln c^o > l_c, \ln d = \ln d^o > l_d \]

\[ L_3 = \int_{-\infty}^{-\Pi_a(q) \ln Z} \phi(\ln a - \Pi_a(q) \ln Z, \nu_c, \ln d - \Pi_d(q) \ln Z) d\nu_c \quad \text{for} \quad \ln a = \ln a^o > l_a, \ln c = l_c, \ln d = \ln d^o > l_d \]

\[ L_4 = \int_{-\infty}^{-\Pi_a(q) \ln Z} \phi(\ln a - \Pi_a(q) \ln Z, \ln c - \Pi_c(q) \ln Z, \nu_d) d\nu_d \quad \text{for} \quad \ln a = \ln a^o > l_a, \ln c = \ln c^o > l_c, \ln d = l_d \]

Another domain is when two of the dependent variables are censored. In these cases, the contributions are the following bivariate conditional log-likelihoods functions:

\[ L_5 = \int_{-\infty}^{-\Pi_a(q) \ln Z} \int_{-\infty}^{-\Pi_c(q) \ln Z} \phi(\nu_a, \nu_c, \ln d - \Pi_d(q) \ln Z) d\nu_a d\nu_c \quad \text{for} \quad \ln a = l_a, \ln c = l_c, \ln d = \ln d^o > l_d \]

\[ L_6 = \int_{-\infty}^{-\Pi_a(q) \ln Z} \int_{-\infty}^{-\Pi_c(q) \ln Z} \phi(\nu_c, \ln c - \Pi_c(q) \ln Z, \nu_d) d\nu_c d\nu_a \quad \text{for} \quad \ln a = l_a, \ln c = l_c, \ln d = l_d \]

\[ L_7 = \int_{-\infty}^{-\Pi_a(q) \ln Z} \int_{-\infty}^{-\Pi_c(q) \ln Z} \phi(\ln a - \Pi_a(q) \ln Z, \nu_c, \nu_d) d\nu_d d\nu_c \quad \text{for} \quad \ln a = \ln a^o > l_a, \ln c = l_c, \ln d = l_d \]

Finally, for observations where none of the dependent variables are censored \((\ln a = \ln d^o, \ln c = \ln c^o, \ln d = \ln d^o)\), the contribution to the likelihood function is:

\[ L_8 = \phi(\ln a - \Pi_a(q) \ln Z, \ln c - \Pi_c(q) \ln Z, \ln d - \Pi_d(q) \ln Z) \]
The total log-likelihood function for the system is therefore:

\[
\log L = \sum_{\ln a = l_a, \ln c = l_c, \ln d = l_d} \log L_1 + \sum_{\ln a > l_a, \ln c > l_c, \ln d > l_d} \log L_2 + \sum_{\ln a > l_a, \ln c = l_c, \ln d = l_d} \log L_3 + \sum_{\ln a > l_a, \ln c > l_c, \ln d = l_d} \log L_4 \\
+ \sum_{\ln a > l_a, \ln c = l_c, \ln d > l_d} \log L_5 + \sum_{\ln a = l_a, \ln c > l_c, \ln d = l_d} \log L_6 + \sum_{\ln a > l_a, \ln c = l_c, \ln d = l_d} \log L_7 + \sum_{\ln a > l_a, \ln c > l_c, \ln d > l_d} \log L_8
\]  

(27)

The existence of discrete components \((\ln a = l_a, \ln c = l_c, \ln d = l_d)\) in likelihood function [27] corresponds to non-zero probabilities of \(\{\ln a = l_a\}\), \(\{\ln c = l_c\}\), or \(\{\ln d = l_d\}\), and these discrete jumps create some computational problems (see Hajivassiliou & Ruud, 1994 for a detailed discussion). Full information estimation can be very computationally expensive in this case, and the source of intractability is often the repeated evaluation of the integral type of functions that characterize the discrete components (Hajivassiliou & Ruud, 1994). Because of such complications, and even though full information estimators are often preferred for their more desirable statistical properties (Greene, 2000), we obtained consistent structural parameter estimates for our model based on a three-stage limited information estimator proposed by Muthén et al (1984, 1997), which is described in the following section.

5.2- The Weighted Least Square Mean Variance (WLSMV) estimator

Our econometric analysis consists of an estimation procedure proposed by Muthén et al (1984, 1997, 2002), and implemented in the program MPLUS. The Weighted Least Squares Mean Variance Estimator (WLSMV) is a minimum distance estimator that provides parameter estimates with robust standard errors. The Minimum Distance estimator (MD) is based on
minimizing the weighted squared distance between the unrestricted reduced form parameters and the (restricted) structural parameters in an overidentified system (Cameron and Trivedi, 2005, Pp.202). Specifically, let \( \hat{\Pi} \) (intercept, slope); and the diagonal elements of \( \hat{\Sigma} \) (or variances) be the first stage parameter estimates; and let the off diagonal elements of \( \hat{\Sigma} \) (or correlations) be the second stage estimates. The estimation procedure is as follows:

1) In the first stage, the reduced form parameter estimates \( \hat{\Pi} \) and the diagonal elements of \( \hat{\Sigma} \) are obtained by maximizing the univariate conditional likelihood described in [27].

The variances of the disturbance of the censored variables are estimated by maximum likelihood assuming a censored normal distribution.

2) In the second stage, the covariance estimates in \( \hat{\Sigma} \) are computed by maximizing the bivariate conditional likelihood described in [27], given the first stage estimates.

3) In the final stage, parameter estimates from the two previous stages are stacked in a vector \( \hat{\kappa} = [\hat{\Pi}, \hat{\Sigma}] \). Similarly, reduced form regression coefficients and covariance matrix are written as a function of structural parameters \( \Pi(q) \) and \( \Sigma(q) \) (as previously defined in relations [25-26]) and stacked in a vector \( \kappa(q) = [\Pi(q), \Sigma(q)] \). Then, structural parameters \( q \) are obtained by minimizing the discrepancy function between the vector of estimates \( \hat{\kappa} \) and the vector depending on the structural parameters \( \kappa(q) \):

\[
\text{Min}_q F(q) = \{\hat{\kappa} - \kappa(q)\} W^{-1} \{\hat{\kappa} - \kappa(q)\}^t
\]

Where \( W \) is a diagonal weight matrix with its diagonal elements equal to the estimated variances

---

\(^{18}\) For a detailed discussion of the Minimum distance estimator, the reader is referred to Ferguson (1958) Rothenberg (1973)
of $\hat{\kappa}$ (Muthén, 1984).

A robust asymptotic covariance matrix for the vector of estimated parameters $\hat{q}$ is:

$$Var (\hat{q}) = n^{-1} [\Delta' W^{-1} \Delta]^{-1} \Delta' W^{-1} V W^{-1} \Delta [\Delta' W^{-1} \Delta]^{-1}$$

Where $\Delta = \frac{\partial \kappa(q)}{\partial q}$, and $V$ is the asymptotic covariance matrix of $\hat{\kappa}$ in the case $W=V$ (Muthén et al, 1997). ¹⁹

Given the Tobit specification of the model, marginal effects are obtained using the estimated coefficients $\hat{\alpha}, \hat{\beta}, \hat{\delta}$ and the predicted probabilities that a value greater than the censoring point is observed for each of the three choice variables. Let $Y = [a, c, d]$ be the vector of choice variables, $Z$ the vector of dependent variables.

Denoting by $\Phi(\cdot)$ the normal CDF, marginal effects for the parameters in double-log are computed based on the following formula:

$$\frac{\partial E[Y|Z]}{\partial Z} = \hat{q} \Phi \left( \frac{\hat{q} Z}{\sigma} \right) \frac{\bar{Y}}{\bar{Z}}$$

(28)

Where $\bar{Y} = [\bar{a} \, \bar{c} \, \bar{d}]$ is the vector of dependent variables at their mean values; $\bar{Z}$ is the vector of exogenous variables of the model (mean values), $\hat{q} = [\hat{\alpha} \, \hat{\beta} \, \hat{\delta}]$ is the vector of coefficients estimate; and $\sigma$ denote the variances. Similarly, for parameters in log-linear form, marginal effects are:

¹⁹ For $W=V$, the problem is to choose the Weighted Least Squares (WLS) estimator $\hat{q}_{WLS}$ to minimize the WLS function $F_{q_{WLS}}$. Letting $\hat{K}$ be the vector of parameters to estimate, the variance for this estimator is such that

$$Var (\hat{q}_{WLS}) = n^{-1} [\Delta' V \Delta]^{-1}$$

where $V$ is the asymptotic covariance matrix for $\hat{K}$.
\[
\frac{\partial E[Y|Z]}{\partial Z} = \hat{q} \Phi \left( \frac{\hat{q} Z}{\sigma} \right) \tilde{Y}
\]  

(29)

Kennedy (1982) shows that a correct measure of the percentage impact of dummy variables on the dependent variable is obtained by using the following formula, which gives the relative effect on \( Y \) of a one unit change in a dummy variable associated with an given dummy variable coefficient estimate \( \hat{q} \):

\[
\hat{d} = E \times p \left[ \hat{q} - \frac{1}{2} \hat{V} (\hat{q}) - 1 \right]
\]  

(30)

Where \( \hat{V} (\hat{q}) \) is the estimated variance of \( \hat{q} \). We compute the marginal effects for dummy variables of our system using the following expression based on equation [28] rather than the direct coefficients, \( \hat{q} \) as follows:

\[
\frac{\partial E[Y|Z]}{\partial Z} = \hat{d} \Phi \left( \frac{\hat{d} Z}{\sigma} \right) \tilde{Y}
\]  

(31)

The final estimated structural model is specified as:

\[
\begin{align*}
\ln a^+ &= \alpha_{a1} + \beta_{a1} \ln PDSI + \beta_{a2} \ln \text{lagPDSI} + \beta_{a3} \ln DL + \beta_{a4} \ln DLsq + \beta_{a5} \ln \text{FILhat} \\
&\quad + \beta_{a6} \ln SLOP + \beta_{a7} \ln ELEV + \beta_{a8} \text{year 87} + \beta_{a9} R_i + u_j \\
\ln c^+ &= \alpha_{c1} + \delta_{c1} \ln a^- + \beta_{c1} \ln \text{PRESUP} + \beta_{c2} \ln \text{POPden} + \beta_{c3} \ln AN + \beta_{c4} \ln AS + \beta_{c5} \ln DL + \beta_{c6} \ln DLsq \\
&\quad + \beta_{c7} \ln \text{FILhat} + \beta_{c8} \ln \text{PRCP} + \beta_{c9} \ln \text{TMAX} + \beta_{c10} \ln SLOP + \beta_{c11} \ln ELEV + \beta_{c12} \text{year 87} + \beta_{c13} \text{year 88} + u_j \\
\ln d^+ &= \alpha_{d1} + \delta_{d1} \ln a^- + \delta_{d2} \ln c^- + \beta_{d1} \ln AN + \beta_{d2} \ln AS + \beta_{d3} \ln DL + \beta_{d4} \ln DLsq + \beta_{d5} \ln \text{FILhat} \\
&\quad + \beta_{d6} \ln \text{PRCP} + \beta_{d7} \ln \text{TMAX} + \beta_{d8} \ln SLOP + \beta_{d9} \ln ELEV + \beta_{d10} R_i + \beta_{d11} \text{year} + u_j
\end{align*}
\]

6- Results

Table 2-3 reports the WLSMV parameter estimates and marginal effects evaluated at the
sample means of the independent variables. We analyze these results in two steps. First, we discuss the results related to the economic returns from investment in pre-suppression and suppression activities, demographics. Second, we discuss topographic and weather coefficient for each equation in the system.

Recall that the C+NVC model developed earlier suggests that $1 spend in suppression ought to reduce damage by $1 at the margin if suppression expenditures are allocated efficiently. From table 2-3 (equation 3), marginal effect of suppression evaluated at the sample means indicates that for every dollar increase in suppression costs, damage will be reduced by 12 cents. Given diminishing returns to suppression, this suggests that there is an over allocation of funding to fire suppression expenditures, all else constant.

Regarding the influence of pre-suppression on suppression expenditures (Table 2-3, equation 2); our results indicate that each dollar invested in pre-suppression reduces suppression expenditures by 3.76 dollar, suggesting an under-allocation of funds to preparedness.\textsuperscript{20} Taken together, the results that there is apparent over-funding of suppression and under-funding of pre-suppression suggests that given a limited budget, a higher percentage of fire management budgets should be allocated to pre-suppression.

Another interesting result from the damage equation relates to the coefficient on total area burned, which indicates that each additional acre included in the containment area engenders, on average, an increase of resource damage value by $1.76. This can be compared to

\textsuperscript{20} We also estimated the model with a smaller sample of the data. That is, from the original sample of 307452 we delete all missing observations and all observations for the period 1985-1994 because damage data observations are mostly missing or recorded as zero. This sub-sample of 207636 observations is use for estimation. We find in this case that $1 invested in suppression reduces the extent of damage by 5 cents and $1 invested in pre-suppression reduces suppression expenditures by $ 3.26. While these new results still indicate an over-allocation of funding to fire suppression, they differ from the ones we found using the complete sample (especially for the returns from investment in suppression) indicating that various results can be observed based on different samples.
the average per-acre damage of $4.71 (based on the values in Table 2-1). Both of these numbers are relatively small, suggesting that the data on resource damage (called NVC in the forest service report forms) may perhaps underestimate the full value of damage. Nonetheless, it is noteworthy that increases in the estimated containment area lead to a relatively low per-acre addition to damage.

Our estimation results also show that an increase in the containment area by 1 acre reduces total suppression costs by $4.81 (Table 2-3, equation 2). Based on this result, we calculate the marginal effect of acreage increase on per acre suppression costs \( \frac{\partial w}{\partial a} \), which amounts to $4.87. \(^{21}\) This result supports our hypothesis that allowing larger acreage reduces the average marginal cost of suppression.

Now consider the effects of other control variables in the regressions. We find that increasing population density negatively affects suppression expenditures instead of positively as hypothesized. It might be the case that increasing population in fire prone areas induces local authorities to increase the number of fire departments, personnel, and equipment for fire protection. This preparedness, not captured in the forest service data, might result in a reduction of the suppression expenditures. Furthermore, wildfire fuels may be more fragmented in highly populated areas, making suppression less costly.

Topographic characteristics of fire areas such as slope, elevation and aspects play a crucial role in fire management because they affect fire severity, initial attack suppression strategies and therefore affect fire fighting expenditures and damage values. For instance, steep

\(^{21}\) In Table 2-3, \( \frac{\partial w}{\partial a} = $4.81. We find marginal effect of acreage increase on per acre suppression costs as follows:

\[
\frac{\partial w}{\partial a} = \left( \frac{\partial c}{\partial a} - \frac{\partial w}{\partial c} \right) \frac{1}{\sigma^2}
\]

where \( \sigma \) and \( \tau \) are the mean values for acreage and costs reported in Table 2-1.
slopes may cause rapid fire-spread and therefore may increase the total acreage burned and also suppression costs and related damages because of the difficulty for firefighter access in steep terrain (Mattsson et al, 2004, Viegas 2004). Our results confirm the positive effect of slope variable on acreage and suppression expenditures but not on resource damage. We find that fires occurring at high elevations result in smaller areas burned, but lead to an increase in suppression cost and resource damage. The literature regarding the interpretation of the effects of elevation level on area burned and costs associated to fire provides mixed results. Some studies argue that large size fire (the most costly in general) can originate at any elevation level, and some others posit that the probability that a fire spreads to become a large fire is lower at high elevations levels (Parsons, 1981, Caprio & Swetnam 1995). These arguments indicate that high elevation does not necessarily lead to smaller acreage burned and costs especially when we look at individual fires, which is the case in this paper. Further, it is important to account for the “time response to a fire” factor, as it will greatly determine the rate of fire spread. Finally, we find that south and north facing aspects increase costs and resource damage from fire, which result is consistent with theory.

Cumulative precipitation and maximum temperature on fire discovery date are included in the model to capture effects of the weather. Our results show, consistent with theory, that rainfall reduces suppression expenditures and net damage value, presumably because it increases fuel moisture. High temperatures on the other hand increase suppression costs. In table 2-3 (equation 1), an important variable that explains area burned is the Palmer’s drought index. For some specific fuel and forest types, studies have found a negative relationship between fire severity and the drought index of the concurrent year and a positive relationship between fire
severity and the drought index of the preceding year (Swetnam and Betancourt, 1998). Our study is consistent with these findings in that concurrent year’s drought index reduces fire severity and area burned by fire.

7-Conclusion

While most cost effectiveness analyses for wildfire suppression are rooted in the cost plus net value change model, effective use of this model requires knowledge about suppression productivity. However, to our knowledge, the existing fire economics literature provides no empirical estimates of the effectiveness of suppression activities in reducing costs and losses associated with wildfires.

This paper provides an empirical basis for the C+NVC model by estimating a wildfire suppression productivity function. Accounting for censoring and endogeneity issues, we construct a simultaneous Tobit model with area burned, suppression expenditure and resource damage jointly determine within a system of equations. Empirical analysis is based upon a three stage limited information estimator known as the Weighted Least Squares Mean Variance (WLSMV).

Among the most interesting results is that at sample means, the marginal dollar of suppression expenditures provides on average only 12 cents worth of damage reduction, suggesting that suppression is over applied. On the other hand, the marginal dollar of pre-suppression expenditures provides $3.76 worth of suppression expenditure reduction. These two results taken together support the idea that pre-suppression is under-applied relative to suppression investment.
Table 2-1: **Summary statistics**  
(N = 30742)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population density</td>
<td>63.9457</td>
<td>261.6049</td>
<td>0.17937</td>
<td>3496.198</td>
</tr>
<tr>
<td>Resource damage</td>
<td>245.34</td>
<td>12585.17</td>
<td>0*</td>
<td>2491128</td>
</tr>
<tr>
<td>Suppression cost</td>
<td>182.279</td>
<td>5850.343</td>
<td>0*</td>
<td>1212722</td>
</tr>
<tr>
<td>Acres burned</td>
<td>54.013</td>
<td>1817.981</td>
<td>0.1</td>
<td>499945</td>
</tr>
<tr>
<td>Pre-suppression cost</td>
<td>133.369</td>
<td>120.2905</td>
<td>0*</td>
<td>1579.071</td>
</tr>
<tr>
<td>Aspect north</td>
<td>0.34808</td>
<td>0.476362</td>
<td>0*</td>
<td>1</td>
</tr>
<tr>
<td>Aspect south</td>
<td>0.41453</td>
<td>0.492642</td>
<td>0*</td>
<td>1</td>
</tr>
<tr>
<td>Slope</td>
<td>23.2778</td>
<td>23.67368</td>
<td>0*</td>
<td>150</td>
</tr>
<tr>
<td>Elevation</td>
<td>4757.38</td>
<td>2733.28</td>
<td>0*</td>
<td>88000</td>
</tr>
<tr>
<td>Delay</td>
<td>0.02707</td>
<td>0.541472</td>
<td>5*</td>
<td>273.9583</td>
</tr>
<tr>
<td>Maximum Temperature</td>
<td>82.9971</td>
<td>11.47739</td>
<td>9.30882</td>
<td>109.0496</td>
</tr>
<tr>
<td>Precipitation</td>
<td>3.35145</td>
<td>7.095132</td>
<td>0*</td>
<td>337.1202</td>
</tr>
<tr>
<td>Fire Intensity Level</td>
<td>1.50535</td>
<td>0.693036</td>
<td>0*</td>
<td>6</td>
</tr>
<tr>
<td>Palmer Drought Severity Index</td>
<td>9.7542</td>
<td>2.3368</td>
<td>3.3841</td>
<td>16.9783</td>
</tr>
</tbody>
</table>

* Changed to 0.0001 to allow for log transformation used in the model estimation
Table 2-2: Data Description

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAMAGE ($lnD$)</td>
<td>USFS estimate of Resource Damage. Generally includes only market value of timber and a crude estimate of recreation value (base year 2000)</td>
</tr>
<tr>
<td>COST ($lnC$)</td>
<td>Suppression cost, (base year 2000)</td>
</tr>
<tr>
<td>ACREAGE ($lnA$)</td>
<td>Total area burned per fire (acres)</td>
</tr>
<tr>
<td>PRE-SUPPRESSION ($lnPRESUP$)</td>
<td>Pre-Suppression costs (base year 2000)</td>
</tr>
<tr>
<td>POPULATION DENSITY ($lnPOPden$)</td>
<td>Population per square miles</td>
</tr>
<tr>
<td>FIRE INTENSITY LEVEL ($lnFILHAT$)</td>
<td>Fire intensity level (estimated value)</td>
</tr>
<tr>
<td>ASPECT ($AS, AN$)</td>
<td>Aspect at ignition (defined as a dummy): 1 if facing south (AS), 0 if not (AN)</td>
</tr>
<tr>
<td>TEMPERATURE ($lnTMAX$)</td>
<td>Maximum daily temperature</td>
</tr>
<tr>
<td>PRECIPITATION ($lnPRCP$)</td>
<td>Precipitation</td>
</tr>
<tr>
<td>SLOPE ($lnSLOPE$)</td>
<td>Slope of the terrain at ignition site.</td>
</tr>
<tr>
<td>DELAY ($lnDL$)</td>
<td>Time between ignition and discovery of the fire.</td>
</tr>
<tr>
<td>DELAY square ($lnDLsq$)</td>
<td>$\ln(DL^2)$</td>
</tr>
<tr>
<td>ELEVATION ($lnELEV$)</td>
<td>Elevation in feet above sea level</td>
</tr>
<tr>
<td>PDSI ($lnPDSI$)</td>
<td>Palmer Drought Severity Index</td>
</tr>
<tr>
<td>Lagged PDSI ($lnlagPDSI$)</td>
<td>Palmer Drought Severity Index (lag value)</td>
</tr>
<tr>
<td>YEAR$_{87}$</td>
<td>Year dummy, ($year87=0$ if year&lt;1987; else $year87=1$)</td>
</tr>
<tr>
<td>YEAR$_{d}$</td>
<td>Year dummy, ($yeard=0$ if 1986-1994; else $yeard=1$)</td>
</tr>
<tr>
<td>$R_i$</td>
<td>Dummy variable for the Forest Services nine regions ($i = 1..9$)</td>
</tr>
</tbody>
</table>
### Table 2-3: WLSMV Estimation results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Equation 1 Dependent = LN (ACRES)</th>
<th>Coefficient</th>
<th>Confidence interval</th>
<th>Marginal effect</th>
<th>Coefficient</th>
<th>Confidence interval</th>
<th>Marginal effect</th>
<th>Equation 2 Dependent = LN (COST)</th>
<th>Coefficient</th>
<th>Confidence interval</th>
<th>Marginal effect</th>
<th>Equation 3 Dependent = LN (DAMAGE)</th>
<th>Coefficient</th>
<th>Confidence interval</th>
<th>Marginal effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTERCEPT</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>LN (ACRES)</td>
<td></td>
<td></td>
<td></td>
<td>-1.737*</td>
<td>(0.295)</td>
<td>[-2.315; -1.159]</td>
<td>-4.81</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>LN (COST)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.663*</td>
<td>(0.021)</td>
<td></td>
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</tr>
<tr>
<td>YEAR1</td>
<td>1.592*</td>
<td>[1.556; 1.628]</td>
<td>3.91</td>
<td>7.875*</td>
<td>(0.472)</td>
<td>[6.951; 8.799]</td>
<td>2629</td>
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<td></td>
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</tr>
<tr>
<td>LN (PPDSI)</td>
<td>-0.018</td>
<td>[-0.097; 0.061]</td>
<td>-0.04</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>LN (PDSILAG)</td>
<td>0.188*</td>
<td>[0.101; 0.274]</td>
<td>0.4</td>
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</tr>
<tr>
<td>LN (DELAY)</td>
<td>-0.054*</td>
<td>[-0.07; -0.038]</td>
<td>-42</td>
<td>-0.166*</td>
<td>(0.026)</td>
<td>[-0.216; -0.116]</td>
<td>-917</td>
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<tr>
<td>LN (DELYS)</td>
<td>0.264*</td>
<td>[0.237; 0.290]</td>
<td>-0.68</td>
<td>0.625*</td>
<td>(0.085)</td>
<td>[0.459; 0.792]</td>
<td>-11.38</td>
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<tr>
<td>LN (FILHAT)</td>
<td>3.358*</td>
<td>[3.333; 3.373]</td>
<td>47</td>
<td>7.523*</td>
<td>(0.987)</td>
<td>[5.588; 9.457]</td>
<td>746.9</td>
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<tr>
<td>LN (ELEV)</td>
<td>-0.382*</td>
<td>[-0.391; -0.374]</td>
<td>-0.001</td>
<td>-0.521*</td>
<td>(0.113)</td>
<td>[-0.743; -0.229]</td>
<td>-0.02</td>
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<tr>
<td>LN (SLOPE)</td>
<td>0.110*</td>
<td>[0.105; 0.115]</td>
<td>0.09</td>
<td>0.231*</td>
<td>(0.033)</td>
<td>[0.167; 0.295]</td>
<td>1.48</td>
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<tr>
<td>LN (PRESUP)</td>
<td></td>
<td></td>
<td></td>
<td>-3.361*</td>
<td>(0.018)</td>
<td>[-3.397; -3.326]</td>
<td>-3.76</td>
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<tr>
<td>LN (POPDEN)</td>
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<td>(0.007)</td>
<td>[-0.149; -0.122]</td>
<td>-4.00E-05</td>
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<tr>
<td>LN (PRCP)</td>
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<td>-0.039*</td>
<td>(0.002)</td>
<td>[-0.044; -0.035]</td>
<td>-1.74</td>
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<tr>
<td>LN (TMAX)</td>
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<td></td>
<td></td>
<td>0.120**</td>
<td>(0.064)</td>
<td>[-0.006; 0.246]</td>
<td>0.22</td>
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<td></td>
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<tr>
<td>ASPECTN</td>
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<td></td>
<td>0.244*</td>
<td>(0.038)</td>
<td>[0.170; 0.318]</td>
<td>0.275</td>
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<tr>
<td>ASPECTS</td>
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<td>0.19*</td>
<td>(0.037)</td>
<td>[0.113; 0.259]</td>
<td>0.203</td>
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<tr>
<td>YEARD</td>
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<td>28.401*</td>
<td>(0.348)</td>
<td>[28.72; 30.09]</td>
<td>5.57E+12</td>
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</tbody>
</table>

Note: Standard errors are in parenthesis

* Significant at 1%
** Significant at 10%
Figure 2-1: C+NVC model (Donovan and Rideout, 2003)

![C+NVC model graph]

Figure 2-2: Distribution of wildfires in the U.S. 1970-2002

Number of fires
Total = 307452
Region 1 = 7077  Region 2 = 16314  Region 3 = 71378  Region 4 = 29496
Region 5 = 72554  Region 6 = 55834  Region 8 = 50049  Region 9 = 4750
Figure 2-3: Resource Damage

Figure 2-4: log-transformed damage

Figure 2-5: log-transformed damage without censored observations

Figure 2-6: Suppression costs

Figure 2-7: log-transformed costs

Figure 2-8: log-transformed costs without censored observations

Figure 2-9: Total acres burned

Figure 2-10: log-transformed acres

Figure 2-11: log-transformed acres without censored observations

Figure 2-12: Scatter plot of Resource damage vs. Costs

Figure 2-13: Scatter plot of Suppression vs. Pre-suppression

Figure 2-14: Scatter plot of Resource damage vs. Acres
THREE ESSAYS ON WILDFIRE ECONOMICS AND POLICY

By

MARIAM D. LANKOANDE

A dissertation submitted in partial fulfillment of
the requirements for the degree of

DOCTOR OF PHILOSOPHY

WASHINGTON STATE UNIVERSITY
School of Economic Sciences

AUGUST 2005

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CHAPTER III

OPTIMAL WILDFIRE INSURANCE IN THE WILDLAND-URBAN INTERFACE IN THE PRESENCE OF A GOVERNMENT SUBSIDY FOR FIRE RISK MITIGATION

1. Introduction

Changing demographics in fire-prone areas, coupled with rising fire expenditures and externalities associated with little fire risk mitigation make wildfire risk management a growing policy concern. Today, roughly 38.6 millions of people live in fire-prone environments, resulting in an average of 900 structures destroyed each year, escalating fire suppression expenditures, and increasing threats to public safety (ISO, 1997, Sampson et al, 2000, Cleaves, 2001).

Migration decisions to rural areas are influenced by various factors including amenities values, privacy, etc (Mckee et al, 2004). Homeowners are drawn to these areas by their preferences for natural settings, spectacular views and location amenities values. However, these new owners of property in wildland-urban interfaces often pay little attention to the natural hazard surrounding their homes, or the risks of financial losses they and the entire taxpaying population might incur from wildfires (Kovacs, 2001). The literature provides evidence that fire risk mitigation generates private risk reduction benefits as well as positive externalities in terms of fire damage risks. Yet, homeowners’ preferences for natural settings, financial and labor costs, and lack of experience represent serious barriers to the adoption and implementation of fire risk mitigation measures (Hodgson 1995, Kovacs 2001, Brenkert et al, 2005). With weak private
incentives for fire prevention, suppression becomes the main tool for wildlife damage reduction. Currently, more than two billion dollars are spent annually on public wildfire suppression and risk mitigation efforts (Ingalsbee, 2000).

Financial loss from wildfire also affects property owner insurance companies, since standard homeowner policies usually cover wildfire damage (Brillinger, 2003). In 1991, roughly $1.7 billion was disbursed in insured losses caused by the Oakland/Berkeley Tunnel Fire (ISO, 1997). More recently, more than $3 billions were paid by the industry following the large wildfires in California in the 1990’s (Kovacs, 2001 (ISO report (1997))). Arguably, the misalignment of homeowners’ incentives with risky choice is encouraged by the current type of insurance contract, which provides a wildfire coverage that is not contingent upon individuals’ risk mitigation effort. Studies have criticized the shortcomings of the current situation and suggested that insurance companies design insurance so that high premiums are correlated with high fire risk in order to discourage people from building in areas with high risk (Reice, 2003). Recognizing that wildfire risk mitigation could be instrumental in reducing average insurance claims, private insurance companies are taking steps towards mitigation-based insurance for communities in fire-prone areas (e.g. in the states of Colorado, Arizona, New Mexico and Nevada). Homeowners’ non-compliance with the insurance program’ requirements might result in either the non-renewal of the coverage policy or a higher premium (USDA, 2003). Hence, the contingent insurance increases the homeowners’ opportunity cost of not taking risk protective measures.
Also in response to increasing wildfire risks in wildland-urban interfaces, state and federal agencies including the U.S. Forest Service are promoting a variety of programs for strengthening risk mitigation incentives (McKee et al, 2004). Cost-sharing programs (CSP) for risk mitigation in the wildland-urban interface are one important part of this incentive policy approach in several states in the Western US. These programs make funding available to counties and communities to subsidize the creation of defensible space around structures, fuel breaks, and the disposal of slash (Steelman et al, 2004). For instance, New Mexico pays up to 75 percent of the total cost of certain risk mitigation measures, and Colorado and Arizona have a 50/50 cost-share program. By reducing the cost of mitigation to homeowners, the subsidy is expected to strengthen incentives for investments in fire protection measures, which in principle will translate into fire damage reduction to participants and their neighbors.

While contingent insurance contracts are expected to realign individuals’ incentives for risk mitigation, and cost share subsidies may offer a solution to the problem of under-provision of mitigation, the effectiveness of these programs at deterring migration to fire prone environments and inducing incentives for mitigation is yet unknown. For instance, the effectiveness of contingent contracts for homeowner policy coverage at discouraging settlements in fire prone environments and inducing more investment in risk mitigation in wildland urban interfaces is yet to be determined. Also, while government subsidy may promote risk mitigation efforts for residents of the urban-wildland interface, it can be criticized on the ground that it might have the unintended
effect of encouraging migration into urban/wildland interfaces (Wright and Rossi 1981, Gardner and El-Abd 1984).

The combination and implementation of government subsidy and mitigation-contingent insurance policies is a new trend that has tended to occur concurrently in the same vicinities.¹ The economic interactions between these two contractual mechanisms are not well understood. For example, it is unclear the extent to which economies of scope are driving the simultaneous development of these programs, or if it is simply because these areas face exceptionally imperfect insurance markets that are independent of potential positive externalities from private wildfire risk mitigation. Furthermore, although it seems relatively obvious that both subsidies and mitigation-contingent contracts will induce more private risk mitigation, it is unclear whether taken together these programs will promote or reduce incentives to migrate to high-risk areas.

These new developments provide an unprecedented setting to examine this interaction. We construct a model of individual migration decision where individuals maximize expected utility defined over attributes of locations. Attributes may include cost of insurance, cost of wildfire risk mitigation, resource damage from wildfire, and the availability of a subsidy for mitigation. We use this model (1) to discuss individuals’ incentives for ‘moving to the hazard’, (2) to examine individuals’ incentives for risk mitigation and (3) to discuss economic efficiency of contingent contracts in the presence of a subsidy for risk mitigation.

¹ For instance, in the states of Colorado, Arizona, New Mexico, cost share programs are available and the mitigation against insurance program is also underway since 2003 (USDA, 2003).
Our analysis shows that standard insurance policies provide inefficiently weak incentive for wildfire risk mitigation by offering a low insurance premium to high-risk landowners. We find on the other hand that insurance contracts contingent upon mitigation effort provide a second best optimum in the sense that homeowners choose a positive level of mitigation that maximizes their private benefit and insurers provide actuarially fair contracts such that each individual is offered a premium of the exact value of her wildfire risk. The analysis shows that an efficient solution is obtained under contingent insurance contract, when government subsidy is chosen such that it covers the external benefits from mitigation.

The next section describes a model of the current standard practice in wildfire insurance in which the same insurance contract is offered to all individuals regardless of their risk level. We discuss the implications of this contract on individuals’ incentive structure. This model is then modified and extended in section 3 to show that, when contingent contracts are offered in the presence of an optimal subsidy, individuals’ incentives are properly aligned with their risky choices. In section 4, we discuss policy implications of our findings.

2. Wildfire insurance contracts: the current setting

The economy consists of N risk-averse households who make the decision (1) to move to location $j$, and if they choose to move to a high-risk area, (2) they decide whether or not to invest in wildfire risk mitigation. Both decisions are made at once,
based on the outcome of households’ utility maximization. Let $V_j$ be the household initial endowment, which represents the location amenity value. Because the relocation area can either be a wildland-urban interface ($w$) or urban vicinity ($u$), households’ expected utility is affected by the risk of wildfire and other costs and losses associated with this risk. Given that individuals are risk averse, we suppose that they account for the cost of insurance and the expected costs for fire risk mitigation in their decision process.

Let $r$ be the fixed cost per unit of mitigation effort $e$ when the homeowner decides to move into a urban/wildland area, so that the total cost of risk mitigation is $C(e) = re$. Denote by $\pi_j(e)$ be the probability of wildfire in location $j = (w, u)$. In the event of a fire, each individual in urban population ($N_u$) incurs a loss $\beta_uD \leq V_u$ with probability $\pi_u(e)$, and each individual in the urban/wildland population ($N_w$) incurs a loss $\beta_uD \leq V_w$ with probability $\pi_w(e)$, such that $0 \leq \pi_u(e) < \pi_w(e) < 1$. The total loss is $D = (\beta_u + \beta_w)D$, and the total population is $N = N_u + N_w$.

### 2.1. Standard insurance (pooling contract) with no subsidy for risk mitigation

Standard homeowners’ insurance policies include coverage for wildfire damage (Insurance Information Institute, Insurance Services Office). Yet, these policies are not contingent upon mitigation effort. Insurers offer the same contract (pooling contract) $(P, Q)$ to all households, with average premium $P$ and compensation (net amount) $Q$ in case

---

of fire. Following Laffont (1990), calculation of the premium $P$ for a pooling contract is based on the following weighted average probability of fire occurrence:

$$
\pi = \pi_u \frac{N_u}{N} + \pi_w \frac{N_w}{N}
$$

Where $\pi_u(e) < \pi_u < \pi_w(e) < \pi_w$, and $\frac{N_u}{N}$, $\frac{N_w}{N}$ are the proportions of people in urban and wildland-urban interfaces. The expected profit of the insurer is:

$$
\Pi = \pi (-Q) + (1 - \pi) P
$$

(1)

Competition drives profit to zero, which implies the premium

$$
P = \frac{\pi}{(1 - \pi)} Q
$$

(2)

Assume that a homeowner buys insurance contract $(P, Q)$. Then, she gets $x_1$ if fire occurs and $x_2$ if no fire such that

$$
x_1 = V_j - re - \beta_j D + Q
$$

And

$$
x_2 = V_j - P
$$

Recalling that unlike insurers, homeowners know and account for the fact that their mitigating behavior affects their wildfire risk such that an individual $N_j$ is subject to

---

3 As we shall see later in the paper, contingent contracts can improve efficiency by strengthening policyholder incentives for risk mitigation. A fundamental question that arises from this is: why aren’t all insurance policies contingent on risk mitigation? We will make the implicit assumption here that contingent contracts require monitoring by the insurance agency, and that monitoring is costly. If monitoring costs a fixed value per contract, then this assumption does not change the marginal results discussed in this paper in substantive qualitative ways.

4 Note that we consider a risk level contingent upon mitigation $\pi_j(e)$ and a risk level non-contingent upon mitigation $\pi_j$. This is because the insurers do not factor in mitigation effort, and in determining expected profit, consider that a homeowner in area $j = u, w$ is subject to risk of wildfire risk $\pi_j$ (non contingent upon mitigation effort); while homeowners know their real exposure to wildfire, also know how their mitigating behavior may affect their wildfire risk, and consider a risk exposure $\pi_j(e)$ (contingent on mitigation).
wildfire risk $\pi_j(e)$, the homeowners’ problem is then to choose the mitigation level $e$ and contract $(P, Q)$ such as to maximize the following expected utility:

$$\text{Max}_{e, (P, Q)} EU = \pi_j(e)U[x_1] + (1 - \pi_j(e))U[x_2]$$

(3)

To derive the first order condition with respect to mitigation level and compensation, we explicitly write expected utility (3) as a function of $e$ and $Q$ by substituting insurance premium $P$, and compensation $Q$ by their respective values and rearranging.

First, since we assume that the homeowner buys the contract $(P, Q)$, we can substitute the value of the premium $P$ (from equation 2) in her expected gain, $x_2$ such that:

$$x_2 = V_j - \frac{\pi}{(1 - \pi)} Q$$

(4)

Then, since $x = V_j - re - \beta_j D + Q$, we can derive the compensation $Q = x_i - V_j + re + \beta_j D$, which is then substituted in equation (4) as:

$$x_2 = V_j - \frac{\pi}{(1 - \pi)}(x_i - V_j + re + \beta_j D)$$

Rearranging, we obtain:

$$x_2 = \frac{V_j - re - \beta_j D\pi}{(1 - \pi)} - \frac{\pi}{(1 - \pi)} x_i$$

(5)

Then, substituting $x_1$ and $x_2$ by their respective values, expected utility (3) can be written as:

$$\text{Max}_{e, (P, Q)} EU = \pi_j(e)U[V_j - re - \beta_j D + Q] + (1 - \pi_j(e))U\left[\frac{V_j - re - \beta_j D\pi}{(1 - \pi)} - \frac{\pi}{(1 - \pi)} x_i\right]$$

(6)
First order condition with respect to $e$ is:

$$\frac{\partial EU}{\partial e} = \pi'(e)U(x_1) - r\pi'(e)U''(x_1) - \pi'(e)U(x_2) - \frac{r}{1-\pi}(1-\pi)(e)U'(x_2) \leq 0 \quad \text{if } e = 0$$

$$= 0 \quad \text{if } e > 0$$

Since we assume that actuarially fair contracts are available, risk averse agents always insure themselves completely to obtain the same utility regardless of the event that occurs (Laffont, 1990). Following Laffont (1990), complete insurance means $u'(x_1) = u'(x_2)$. This implies that the first order condition with respect to $e$ can be written:

$$\frac{\partial EU}{\partial e} = -r \pi'(e)U'(x_1) - \frac{r}{1-\pi}U'(x_2) + \frac{r}{1-\pi} \pi'(e)U'(x_2)$$

$$\frac{\partial EU}{\partial e} = \left(-\pi'(e) - \frac{1}{1-\pi} + \frac{1}{1-\pi} \pi'(e)\right) rU'(x_2)$$

$$- \left(1 - \pi \pi'(e)\right) rU'(x_2) < 0 \quad \text{if } e^{*} = 0$$

$$= 0 \quad \text{if } e^{*} > 0$$

(7)

Since $U'(x_2) > 0$, $1 - \pi \pi'(e) > 0$, $r > 0$; we must have that the level of mitigation is zero ($e^{*} = 0$) regardless of the location chosen: urban or urban/wildland.  

Our first, perhaps most obvious result is:

**Proposition 1:** Standard insurance is ineffective at inducing incentive for wildfire risk mitigation.

Given the chosen level of mitigation $e^{*}$, the optimality condition for $Q$ is:

---

5 Note that the absence of incentive for mitigation (i.e. $e^{*} = 0$) is a reasonable result here because we assume that homeowners insure themselves completely (no deductible).

6 Recall that $\chi = \beta_{D} + Q$ is a function of $Q$ so that the second element of expected utility (6) can also be derived with respect to $Q$. 

\[
\frac{\partial EU}{\partial Q} = \pi_j(e^*)U'(x_j) - (1 - \pi_j(e^*)) \frac{\pi}{(1 - \pi)} U'(x) \\
= \frac{\pi_j(e^*)}{(1 - \pi_j(e^*))} \frac{U'(x)}{U'(x)} - \frac{\pi}{(1 - \pi)} \tag{8}
\]

Because \(\pi_x(e^*) < \pi_u < \pi\), relation [8] implies

\[
\frac{\pi_x(e^*)}{1 - \pi_x(e^*)} \frac{U'(x)}{U'(x)} < \frac{\pi}{1 - \pi} \implies MRS_{x_1 x_2} < \frac{\pi}{1 - \pi}
\]

which can also be written as:

\[
\frac{\pi_x(e^*)}{1 - \pi_x(e^*)} Q < \frac{\pi}{1 - \pi} Q \iff P_x < P \tag{9}
\]

Similarly, for high-risk group \(\pi_x > \pi_x(e^*) > \pi\), equation [8] implies

\[
\frac{\pi_x(e^*)}{1 - \pi_x(e^*)} \frac{U'(x)}{U'(x)} > \frac{\pi}{1 - \pi} \implies MRS_{x_1 x_2} > \frac{\pi}{1 - \pi}
\]

Or

\[
P_w > P \tag{10}
\]

Results [9] and [10] show that the pooling contract \((P, Q)\) is not an optimal choice for residents or prospective residents of the wildland-urban interface.

**Proposition 2:** *Standard insurance promotes building in fire-prone environment by offering high-risk individuals (defined as those living in the urban-wildland interface) a premium \(P\) smaller than their wildfire risk \(P_w\).*

Propositions 1-2 highlight two important issues arising under the standard insurance policy coverage. First, we find that since the contracts offered do not factor in
homeowners’ mitigation efforts and yet provide coverage for wildfire damage, homeowners have little incentive for investing in risk mitigation. Second, we find that under the standard policy coverage, insurers offer high-risk households a premium lower than their wildfire probability, thus promoting further building in fire-prone environments. A company offering such contract risks losing low-risk policyholders, which is a common adverse selection result given non-contingent contracts.

An additional issue that relates to social optimality concerns the externalities resulting from little or no mitigation where it would be appropriate. When the homeowner mitigates wildfire risk on her land, she is likely to mitigate fire risk on her neighbors’ land. And because some benefits of wildfire risk mitigation are extended to neighboring landowners, cost-sharing programs could be justified to effectively induce landowners to internalize these benefits to neighbors. Next, we discuss the introduction of a subsidy in the context of a standard contract.

2.2. Standard pooling insurance contract with subsidy for wildfire risk reduction

One common government intervention approach to encourage positive external benefits is the use of subsidies. Suppose that the cost of mitigating is shared by a government agency such that homeowners pay a percentage \( \alpha \) for of the total cost such that their expected cost is \( (\alpha \times r \times e) \), where \( \alpha \) can take values \( (\alpha = 0, 0 < \alpha < 1, \alpha = 1) \). Let \( (1-\alpha) \) be the subsidy provided by the agency. If \( \alpha = 0 \), then the full cost of fire risk mitigation is covered by the CSP subsidy, and households pay nothing. If \( 0 < \alpha < 1 \), then the cost of fire risk mitigation is partially covered by the CSP subsidy, in which case only a partial
externalization of the costs exists. Finally, if $\alpha=1$, the full cost of fire risk mitigation is borne by households. Given this specification, homeowner gets $x_3$ if a fire occurs and $x_4$ is no fire occurs, such that

$$x_3 = V_j - \alpha re - \beta_j D + Q$$

And

$$x_4 = V_j - P = \frac{V_j - \alpha re - \beta_j D \pi}{(1 - \pi)} - \frac{\pi}{(1 - \pi)}(x_i).$$

The household chooses the optimal contract to maximize the expected utility:

$$\max_{e, Q, P} EU = \pi_j(e) U \left[ V_j - \alpha re - \beta_j D + Q \right] + (1 - \pi_j(e)) U \left[ \frac{V_j - \alpha re - \beta_j D \pi}{(1 - \pi)} - \frac{\pi}{(1 - \pi)}(x_i) \right]$$

(11)

The optimal mitigation level and insurance contract are identical to the previous case, with first order conditions shown by equations 7, 9, 10. Homeowners choose to exert zero mitigation ($e^*=0$) with the subsidy. This suggests that making a subsidy available in the standard insurance contract context is not an effective approach to creating incentives for fire prone environment residents (or prospective residents) to mitigate the risk of wildfire. For a subsidy to have any effect in this framework, we would need to relax our assumption of full insurance to make the homeowner liable for covering some of her expected loss from wildfire. In fact, if there is a deductible, that is, if landowners have to pay say, $X$, of the damage to their property in the event of a fire under a standard contract, then they will have some limited incentive to mitigate the risk.

**Proposition 3:** Subsidies are likely to be ineffective at inducing private wildfire risk mitigation under standard pooling contracts.
As summarized in propositions 1-3 standard insurance policies present some challenging issues in terms of incentive for wildfire risk mitigation. Yet, the insurance industry has the potential, by working closely with governments and individuals, to properly align individuals’ incentives with risky choices. Insurances companies are acting upon the limitations of the standard insurance policy by moving towards insurance contracts that are contingent on policyholder risk mitigation.

3. Efficient wildfire insurance in the presence of government intervention through a subsidy for risk mitigation

In this section, we analyze the implications of insurance contracts contingent upon investment in fire risk mitigation in terms of incentives for mitigation and disincentives for ‘moving to the hazard’. We discuss the efficiency of this type of contract with and without subsidy programs.

3.1. Contingent insurance contracts for wildfire risk

The economy consists of the same group of N agents introduced previously. Insurers offer a contract contingent on effort \( e \), \((P_j(e),Q_j(e))\) with premium \( P_j(e) \), and compensation \( Q_j(e) \) in case of fire. The expected profit of the insurer is:

\[
\Pi = \pi_j(e)(-Q_j(e)) + (1 - \pi_j(e)) P_j(e)
\]

(12)

Competition drives profit to zero, which implies the actuarially fair premium
Given that homeowners buy contracts \((P_j(e), Q_j(e))\), they get \(x_5\) if a fire occurs and \(x_6\) is no fire such that:

\[
x_5 = V_j - r e - \beta_j D + Q_j(e)
\]

\[
x_6 = V_j - r e - P_j(e)
\]

Following the same reasoning as before, we substituting premium \(P_j(e)\) and compensation \(Q_j(e)\) by their respective values, \(x_6\) is written as:

\[
x_6 = V_j - \frac{\pi_j(e)}{(1 - \pi_j(e))} Q_j(e)
\]

\[
= V_j - \frac{\pi_j(e)}{(1 - \pi_j(e))} (x_5 - V_j + r e + \beta_j D)
\]

\[
= \frac{V_j - re - \beta_j D \pi_j(e)}{(1 - \pi_j(e))} - \frac{\pi_j(e)}{(1 - \pi_j(e))} x_5.
\]

This time, both insurers and homeowners account for wildfire risks contingent upon mitigation in their respective objective functions. In this case, the homeowner’s problem is to find the optimal contract \((P_j(e), Q_j(e))\) given the mitigation level \(e\) that they choose to maximize the following expected utility:

\[
\text{Max}_{e, Q_j(e)} \text{EU} = \pi_j(e) U \left[V_j - r e - \beta_j D + Q_j(e)\right] + (1 - \pi_j(e)) U \left[\frac{V_j - re - \beta_j D \pi_j(e)}{(1 - \pi_j(e))} - \frac{\pi_j(e)}{(1 - \pi_j(e))} x_5\right]
\]

First order condition with respect to \(e\) is:

\[
\frac{\partial \text{EU}}{\partial e} = \pi_j'(e) U (x_5) - \pi_j(e) \left[r + Q_j'(e)\right] U'(x_5)
\]

\[
- \pi_j'(e) U (x_6) - (1 - \pi_j(e))(r + P_j'(e))(U'(x_6)) = 0 \quad \text{if} \quad e^r > 0
\]

\[
< 0 \quad \text{if} \quad e^r = 0
\]
The contingent insurance contract allows \( u'(x_s) = u'(x_6) \) and therefore the first condition with respect to \( e \) is:

\[
\frac{\partial \mathcal{U}}{\partial e} = -\pi_j(e) \left[ \mathcal{U}'(x_s) - (r + P'_j(e)) \mathcal{U}'(x_s) + \pi_j(e)(P'_j(e)) \right] U'(x_s) = 0 \quad \text{if} \quad e^p > 0
\]

\[
< 0 \quad \text{if} \quad e^p = 0
\]

\[
r + \pi_j(e^p) Q_j'(e^p) + (1 - \pi_j(e^p))( P'_j(e^p) ) = 0 \quad \text{if} \quad e^p > 0
\]

\[
< 0 \quad \text{if} \quad e^p = 0
\]

(16)

Because all elements on the left hand side of equation [16] are non-negative, we must have that the optimal level of mitigation is non-zero \((e^p > 0)\). In other words, homeowners choose non negative level of mitigation \(e^p > 0\), such that their marginal cost for risk mitigation equals their marginal benefit:

\[
r = -\pi_j(e^p) Q_j'(e^p) - (1 - \pi_j(e^p))( P'_j(e^p) )
\]

(17)

Given the optimal private mitigation level \(e^p > 0\), the compensation \(Q_j(e^p)\) is derived from the following first order condition:

\[
\frac{\partial \mathcal{U}}{\partial Q_j(e^p)} = \pi_j(e^p) U'(x_s) - (1 - \pi_j(e^p)) \frac{\pi_j(e^p)}{(1 - \pi_j(e^p))} U'(x_s) = 0
\]

\[
\Rightarrow U'(x_s) = U'(x_6)
\]

\[
\Rightarrow x_s = x_6
\]

\[
\Rightarrow V_j - re^p - \beta_j D + Q_j(e^p) = V_j - re^p - \frac{\pi_j(e^p)}{(1 - \pi_j(e^p))} Q_j(e^p)
\]

\[
\Rightarrow Q_j'(e^p) = (1 - \pi_j(e^p)) \beta_j D
\]

(18)

Substituting optimal compensation \(Q_j(e^p)\) from equation [17] in equation [13], we get

\[
P_j(e^p) = \pi_j(e^p) \beta_j D
\]

(19)
Combination of results [18] and [19] constitute the following optimal insurance contract for households

\[
\left( P_j^\prime(e^\prime), Q_j^\prime(e^\prime) \right) = \left( \pi_j(e^\prime) \beta_j D, (1 - \pi_j(e^\prime)) \beta_j D \right)
\]  

(20)

Substituting the optimal contract in the first order condition [18], we can rewrite it as:

\[-r = \pi_j(e^\prime) Q_j^\prime(e^\prime) + (1 - \pi_j(e^\prime))( P_j^\prime(e^\prime))
\]

\[r = -\pi_j(e^\prime) \beta_j D.
\]  

(21)

**Proposition 4**: Under a contingent contract, a homeowner chooses mitigation level \(e^p > 0\) and insurers offer a premium of the exact value of her private wildfire risk.

Keys findings from the implementation of contingent contracts are the induction of incentives for mitigation and the realignment of incentives with risky choices by the provision of a contract that reflect individuals’ risk. For instance, assuming that the risk of wildfire is zero in urban area, a homeowner in such vicinity suffers a loss \(\beta_u D\) with probability \(\pi_u(e^\prime) = 0\) and therefore does not need a wildfire coverage included in her policy.\(^7\) A wildland-urban interface resident on the other hand suffers a loss \(\beta_w D\) with probability \(\pi_w(e^\prime) > 0\). Such homeowner chooses to mitigate until her private marginal benefit in terms of damage reduction equals the unit cost of mitigation at the margin

\[r = -\pi_w(e^\prime) \beta_w D.
\]

\(^7\) Here we are discussing specifically the part of the insurance premium that covers wildfire damage. Note that a complete policy would offer a total premium \(TP\) which include not only the premium \(P_j^p(e)\) for wildfire coverage but also a premium \((I)\) for coverage of other elements that the homeowners chooses to include in her policy such that total premium could be written \(TP = P_j^p(e) + I\).
The following contract is offered \( (P_r(e^r), Q_r(e^r)) = (\pi_r(e^r) \beta_r D_r(1 - \pi_r(e^r))\beta_r D) \), which reflects the landowner’s mitigation level.

Results [20] and [21] show that implementation of contingent contracts strengthen private incentive for investments in fire protection measures and deter new developments in fire hazard areas. However, this result corresponds to a second best optimum. A homeowner in the urban/wildland interface chooses the level of mitigation that optimizes her private benefits without consideration for risk reduction provided to her neighbors. In her expected utility, the homeowner only tries to reduce privately born resource damage \((\beta, D)\) in the case of a fire, while a higher level of mitigation could reduce not only privately born damage \((\beta, D)\), but also damage to others \((1 - \beta) D\).

In figure 3-1.A, we represent the optimal private level of mitigation obtained in condition [21]. Since the homeowner does not account for the benefit of her mitigating action on the others, she chooses a level of mitigation \(e^0\) such that private net benefit are maximized, that is when marginal private benefits equals marginal cost, MPB = MC (point A). For the same level of mitigation, figure 3-1.A shows that social efficiency is not achieved because marginal social benefit is higher than the marginal cost, MSB>MC, (point C).

**Figure 3-1:** Optimal private and social mitigation level in the presence of positive externalities provided by fire risk mitigation

**Figure 3-1.A:** Optimal private solution  
**Figure 3-1.B:** Optimal social solution
Social efficiency can be obtained by choosing a level $e^* > e^p$ of mitigation such that the marginal external benefits from risk mitigation (MEB) are privately internalized and the socially efficient solution is in point B (figure 3-1.B). Mathematically, the social optimization problem is:

$$\text{Max}_{e, Q_e} \{ E[\text{Net Private Benefits (e)}] + E[\text{External Benefits (e)}] \}$$

$$= \left\{ \pi_j(e)U[V_j - r e - \beta_j D + Q_j(e)] \right\} + \left\{ \pi_j(e)U[-(1 - \beta_j)D] \right\}$$

First order conditions show that the socially optimal solution is to choose level of mitigation $e^*$ is such that:

$$r = \left\{ - \pi_j^*(e^*) \beta_j D \right\} + \left\{ - \pi_j^*(e^*) (1 - \beta_j) D \right\} = - \pi_j^*(e^*) D$$

or

$$\text{MC} = \text{MPB} + \text{MEB} = \text{MSB}$$

as displayed in figure 3-1.B

Given the mitigation level $e^*$, the following contingent contracts are available

$$(P_j^*(e^*), Q_j^*(e^*)) = (\pi_j(e^*) D, (1 - \pi_j(e^*)) D)$$

Note that at the socially optimal level of mitigation $e^*$, private costs are higher than benefits (MC > MPB at point B in figure 3-1.B) suggesting that homeowners need more
incentives to move from the competitive level of mitigation, $e^0$, to the desired level of mitigation, $e^*$. 

**Proposition 5:** Contingent insurance contracts strengthen homeowner incentives for fire risk mitigation. However, private mitigation effort is still suboptimal.

Proposition 5 suggests that economic efficiency can be improved by encouraging more risk mitigation. This can be done through the use of the cost share program subsidy that reduces the cost of fire risk mitigation to homeowners. The question we address next is from a policymaker perspective to calculate the subsidy level such that homeowners choose the socially optimal level of mitigation $e^*$. 

**3.2-Optimal subsidy for efficient contingent insurance contract**

Government interventions through subsidies are often justified by the presence of market failure. In the present context, wildfire risk mitigation provides positive externalities in terms of expected damage reduction to neighbors. But, because homeowners fail to account for these benefits in their objective function, a free market results in under-provision of risk mitigation. Economic theory suggests that the choice of a subsidy that amounts to the size of the externality can restore efficiency. Let $(1-\alpha)$ be the subsidy such that the homeowner now pays $\alpha r$ and the subsidy covers $(1-\alpha) r$. Homeowners get $x_7$ and $x_8$ respectively in cases of fire and no fire such that $x_7 = V_j - \alpha r e - \beta_j D + Q_j(e)$ and $x_8 = V_j - \alpha r e - P_j(e)$. 

The private optimization problem is:

\[
\text{Max} \quad EU = \pi'(e)U[x_i] + (1 - \pi'(e))U[x_s]
\]  

(25)

Optimality conditions show that the level of mitigation \(e^*\) is chosen such that:

\[
\alpha r = -\pi'(e^*)\beta_j D
\]  

(26)

Substituting external benefits from condition [23] into [26], we get the optimal subsidy:

\[
(1 - \alpha)r = -\{\pi'(e^*)(1 - \beta_j)D\}
\]  

(27)

Condition [27] shows that for the homeowner to exert socially efficient mitigation level \(e^*\), the optimal subsidy should equal the external benefit to society from additional mitigation effort as illustrated in figure 3-2.

**Proposition 6:** When the subsidy for fire risk mitigation is set to equal the net social gain from fire risk reduction, homeowners exert the socially efficient level of mitigation \(e^*\) and insurers offer insurance contracts that reflect individuals’ risks.

**Figure 3-2:** Socially efficient solution with optimal subsidy
4. Discussion

Wildfire risk in the WUI is a growing problem with high social and economical consequences, and affects a variety of stakeholders including fire protection agencies, homeowners, governments, and insurance companies. Barriers to the effective implementation of risk management policies range from free-riding behavior related to risk mitigation, to underinsurance in fire prone areas. In response, some local governments and insurance companies are moving toward using incentive-based approaches to promote private wildfire risk mitigation efforts. Insurers are implementing insurance contracts contingent upon mitigation effort, and various government agencies are providing cost-share programs for wildfire risk mitigation.

In this paper, we investigate the effect of standard and contingent insurance contracts and government subsidies on incentives for risk mitigation by WUI residents, and the incentives for settlement in fire prone areas. We construct a model of migration
decisions, where individuals choose the location that provides the highest expected utility given a range of location specific attributes including insurance contracts, and cost sharing program subsidies for fire risk mitigation. The effectiveness of non-contingent and contingent insurance contracts is examined in the presence (or not) of government cost share subsidy.

Our analysis shows that offering mitigation-contingent insurance contracts to residents (or prospective residents) in the wildland-urban interface improves incentives for mitigation as well as incentive related to development in fire-prone areas. Residents of urban vicinities do not share the burden of wildfire risk. Contingent contracts increase the sum of mitigation costs and premiums to owners of fire-prone property, thereby inducing fewer people to move into fire prone areas and increasing the risk mitigation efforts of those who do. Because wildfire ignores property boundaries, risk mitigation by one property owner can reduce the wildfire risk faced by neighbors. The fact that investments in risk mitigation generate positive externalities can be viewed as a justification for public support of mitigation efforts on private land. Our analysis shows that in the presence of standard insurance contracts, subsidies are ineffective for inducing private risk mitigation efforts, whereas they are more effective under contingent contracts. Furthermore, whereas standard contracts in conjunction with subsidies induce too much development in fire-prone areas, the combination of contingent contracts and subsidies of the appropriate size correct this problem.
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