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An Econometric Model of Wildfire Suppression Productivity

By

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Abstract

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. This paper 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).

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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, 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 simultaneous system of regression equations. The analysis is conducted using the National Interagency Fire Management Integrated Database (NIFMID) data and supporting data from other sources.

Our results show that an increase in suppression expenditures reduces resources damage. Further, our estimates imply that that returns from investment in suppression at the margin are small compared to the suppression investment, suggesting an over-allocation of funding for 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. As discussed below, these results are intuitively plausible and intriguing on a qualitative level, but care should be taken in terms of the quantitative results because the definition of *damage* as defined in the data collection mechanism is limited in scope and has changed over the years.

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.[1] 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:

$$c + d = \varepsilon_s w(\varepsilon_a a; \mathbf{Z}_s)s + \varepsilon_d d(\varepsilon_a a, s; \mathbf{Z}_d) \tag{1}$$

Where

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

[1] 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 $\mathbf{Z}_s$ that includes pre-suppression inputs applicable for a particular fire, and other determinants of marginal suppression costs.
- a is fire the chosen target acreage (containment area) for suppression efforts. The actual ex-post fire acreage is $\varepsilon_a a$ where ε_a is a random variable with mean and variance $\varepsilon_a \sim (1, \sigma_a^2)$.
- 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 $\mathbf{Z}_d$. The error term is distributed $\varepsilon_d \sim (1, \sigma_d^2)$

Assume that at the margin, allowing a larger containment area is expected ex ante to reduce the marginal cost of suppression, so that $\partial w / \partial a < 0$, but that increased acreage increases damage, so that $\partial d / \partial a > 0$. 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 $\partial d / \partial s < 0$. Assume also 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:

$$\mathrm{E}[\mathrm{c} + \mathrm{d}] = w(a; \mathbf{Z}_s)s + d(a, s; \mathbf{Z}_d) \tag{2}$$

Assuming that the second-order conditions for a maximum hold, the first-order conditions to maximize E [c +d] are:

$$\frac{\partial\, \mathrm{E}[\mathrm{c}+\mathrm{d}]}{\partial\, s} = w + \frac{\partial\, d}{\partial\, s} = 0\,, \quad \text{or}$$
$$w = -\frac{\partial d}{\partial s} \tag{3}$$

$$\begin{aligned} \frac{\partial \;\; \mathrm{E} \;\; [\mathrm{c}+\mathrm{d}]}{\partial \;\; a} &= \frac{\partial w}{\partial a} s + \left(\frac{\partial d}{\partial s} \times \frac{\partial s}{\partial a} \right) = 0 \\ &= \frac{\partial w}{\partial a} s + w \frac{\partial s}{\partial a} = 0. \end{aligned} \tag{4}$$

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:

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

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, $\partial d / \partial (ws) < -1$ means that one dollar of suppression reduces damage by more than one dollar at the margin and implies too little suppression; $\partial d / \partial (ws) > -1$ 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

$$s^* = s(\mathbf{Z}_s, \mathbf{Z}_d) \tag{6}$$

$$a^{*} = a(\mathbf{Z}_s, \mathbf{Z}_d) \quad (7)$$

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

$$\begin{aligned} a^{o} &= \varepsilon_a a(\mathbf{Z}_s, \mathbf{Z}_d) \\ &= \varepsilon_a a^{*} \end{aligned} \quad (8)$$

$$\begin{aligned} c^{o} &= \varepsilon_s w(\varepsilon_a a^{*}; \mathbf{Z}_s) s^{*} \\ &= \varepsilon_s w(a^{o}; \mathbf{Z}_s) s^{*} \end{aligned} \quad (9)$$

$$d^{o} = \varepsilon_d d(\varepsilon_a a^{*}, s^{*}; \mathbf{Z}_d) \quad (10)$$

$$= \varepsilon_d d(a^{o}, (c^{o} / \varepsilon_s w(a^{o}; \mathbf{Z}_s)); \mathbf{Z}_d), \quad (11)$$

where $c^{o} / \varepsilon_s w(\varepsilon_a a^{*}; \mathbf{Z}_s) \equiv s^{*}$ 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 *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^{0}.

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 ε_a and ε_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 **Z = [Z$_a$ Z$_s$ Z$_d$]**, which contains all available exogenous variables, and let $\mathbf{Z}^{\beta_j} = \prod_{i=i}^{k_j} Z_i^{\beta_j}$ represent the Cobb Douglas functional form for the j_{th} equation.

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

$$a^o = e^{\alpha_a}\mathbf{Z}^{\beta_a}\varepsilon_a \tag{12}$$

so that the log-linear estimable equation is

$$\ln a^o = \alpha_a + \beta_a \ln \mathbf{Z} + u_a \tag{13}$$

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

To specify c^0 (equation 9), the functional form of the (unobserved) marginal cost of suppression effort must be specified. Let

$$\begin{aligned} w(a^o; \mathbf{Z}_s) &= e^{\alpha_{w1}}\mathbf{Z}^{\beta_{w1}}(a^o)^{\delta_w}\text{, or} \\ &= e^{\alpha_{w1}}\mathbf{Z}^{\beta_{w1}}e^{\alpha_a}\mathbf{Z}^{\beta_a}\varepsilon_a \\ &= e^{\alpha_w}\mathbf{Z}^{\beta_w}\varepsilon_a \end{aligned} \tag{14}$$

where $\alpha_w = \alpha_{w1} + \alpha_a$ and $\beta_w = \beta_{w1} + \beta_a$.

Unobserved suppression effort is

$$s^* = e^{\alpha_s}\mathbf{Z}^{\beta_s}. \tag{15}$$

Putting the marginal cost and effort functions together, the suppression cost function (equation 9) then becomes

$$
\begin{aligned}
c^{o} &= \varepsilon_{s} w(a^{o}; \mathbf{Z_s}) s^{*} \\
&= e^{\alpha_{\mathbf{w1}}} \mathbf{Z}^{\beta_{\mathbf{w1}}} (a^{o})^{\delta_{w}} e^{\alpha_{\mathbf{s}}} \mathbf{Z}^{\beta_{\mathbf{s}}} \varepsilon_{a} \varepsilon_{s} \\
&= e^{\alpha_{c}} (a^{o})^{\delta_{c}} \mathbf{Z}^{\beta_{\mathbf{c}}} \varepsilon_{a} \varepsilon_{s} \qquad (16)
\end{aligned}
$$

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

$$\ln c^{o} = \alpha_{\mathbf{c}} + \delta_{c} \ln a^{o} + \beta_{c} \ln \mathbf{Z} + u_{c} \qquad (17)$$

where $u_c = \ln \varepsilon_a \varepsilon_s$ has mean zero and is correlated with u_a.

The damage function [10] is specified as:

$$
\begin{aligned}
d^{o} &= e^{\alpha_{d1}} (a^{o})^{\delta_{d1}} (c^{o} / \varepsilon_{s} w(.))^{\delta_{d2}} \mathbf{Z_d}^{\beta_{\mathbf{d1}}} \varepsilon_{d} \\
&= e^{\alpha_{d1}} (a^{o})^{\delta_{d1}} (c^{o})^{\delta_{d2}} (e^{\alpha_{w}} \mathbf{Z}^{\beta_{w}})^{-\delta_{d2}} \mathbf{Z}^{\beta_{d1}} \varepsilon_{s}^{-\delta_{d2}} \varepsilon_{d} \qquad (18) \\
&= e^{\alpha_{d}} (a^{o})^{\delta_{d1}} (c^{o})^{\delta_{d2}} \mathbf{Z}_{d}^{\beta_{d}} \varepsilon_{d1} \qquad (19)
\end{aligned}
$$

Where $\alpha_d = \alpha_{d1} + \alpha_w$, $\beta_d = \beta_{d1} + \beta_w$, $\beta_d = \beta_{d1} + \beta_w$, and $\varepsilon_{d1} = \varepsilon_s^{-\delta_{d2}} \varepsilon_d$.

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.[2] If testing shows that a_o and/or c^o are correlated with ε_{d1}, these two variables can be replaced with estimated values of a^* and c^*.

The log linear form of equation [19] is then

$$\ln d^{o} = \alpha_{d} + \delta_{d1} \ln a^{o} + \delta_{d2} \ln c^{o} + \beta_{d1} \mathbf{Z}_{d} + u_{d} \qquad (20)$$

[2]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 $u_d = \ln \varepsilon_s^{-\delta_{d2}} \varepsilon_{d1} \sim N(0, \sigma_{u_d}^2)$. Given the interpretation of $a^o / a^* = \varepsilon_a$ as relating to acreage beyond the planned containment area, endogeneity of a^o in equations [15] and [20] suggests that ε_a is correlated with costs and damage with escapes. Further, because ε_s is an element of ε_{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 ε_a and ε_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 are 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.

Observed resource damage *(d^o)* values for the years 1985 to 1994 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 censoring 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.[3] 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^o)* 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

[3] 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.

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.

The final endogenous variable is total wildfire acreage *(a^o).* 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, and 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. For a given fire, suppression costs and damage are jointly determined, and 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 $\boldsymbol{Z_j}$ $(j=a, c, d)$ 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.[4] 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 annual and lagged values. Both variables *(PDSI* and *PDSIlag*)[5] 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

[4] 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.
[5] We rescaled the average annual PDSI (=PDSI+10) in order to consider the logarithm

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 *(DLsq)* 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.[6]

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 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

[6] 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.

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 $i = 1,\ldots, 9$).*

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

5- Estimation approach

To address the data characteristics described above, we specify a simultaneous Tobit system, 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:

$$\ln a^o = \boldsymbol{\alpha}_{\mathbf{a}} + \beta_{\mathbf{a}} \ln \mathbf{Z}_{\mathbf{a}} + u_a$$

$$\ln a = \begin{cases} \ln a^o & if \quad \ln a^o > l_a \\ l_a = \ln(0.1) & otherwise \end{cases} \quad (21)$$

Where u_a is censored normal with mean zero and variance σ_a^2, α_a and β_a and are the coefficients to be estimated, and $\mathbf{Z_a}$ 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:

$$\ln c^o = \alpha_{\mathbf{c}} + \delta_c \ln a^o + \beta_c \ln \mathbf{Z_c} + u_c$$

$$\ln c = \begin{cases} \ln c^o & if \quad \ln c^o > l_c \\ l_c = \ln(0.0001) & otherwise \end{cases} \quad (22)$$

Where u_c is censored normal with mean zero and variance σ_c^2, α_c and δ_c are the coefficients to be estimated, and $\mathbf{Z_c}$ is the vector of exogenous variables.[7]

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

$$\ln d^o = \alpha_d + \delta_{d1} \ln a^o + \delta_{d2} \ln c^o + \beta_{\mathbf{d}} \ln \mathbf{Z_d} + u_d$$

$$\ln d = \begin{cases} \ln d^o & if \quad \ln d^o > l_d \\ l_d = \ln(0.0001) & otherwise \end{cases} \quad (23)$$

Where u_d is censored normal with mean zero and variance σ_d^2; δ_d and β_d are the coefficients to be estimated, and $\mathbf{Z_d}$ 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:

[7] In order to calculate the log transformation of c^o (and d^o below), zeros were set to 0.0001.

$$\Psi = \begin{bmatrix} \sigma_a^2 & \rho_{ac}\sigma_a\sigma_c & \rho_{ad}\sigma_a\sigma_d \\ \rho_{ca}\sigma_c\sigma_a & \sigma_c^2 & \rho_{cd}\sigma_c\sigma_d \\ \rho_{da}\sigma_d\sigma_a & \rho_{dc}\sigma_c\sigma_d & \sigma_d^2 \end{bmatrix}$$

The structural model [20-22] is:

$$\begin{cases} \ln a = \alpha_{\mathbf{a}} + \beta_{\mathbf{a}} \ln \mathbf{Z}_{\mathbf{a}} + u_a \\ \ln c = \alpha_{\mathbf{c}} + \delta_c \ln a^o + \beta_c \ln \mathbf{Z}_{\mathbf{c}} + u_c \\ \ln d = \alpha_d + \delta_{d1} \ln a^o + \delta_{d2} \ln c^o + \beta_{\mathbf{d}} \ln \mathbf{Z}_{\mathbf{d}} + u_d \end{cases}$$

Given $k = a, c, d$, this can also be written as:

$$\begin{bmatrix} 1 & 0 & 0 \\ -\delta_c & 1 & 0 \\ -\delta_{d_1} & -\delta_{d_2} & 1 \end{bmatrix} \begin{bmatrix} \ln a \\ \ln c \\ \ln d \end{bmatrix} = \begin{bmatrix} \alpha_a & \beta_a \\ \alpha_c & \beta_c \\ \alpha_d & \beta_d \end{bmatrix} \begin{bmatrix} 1 \\ \ln \mathbf{Z}_{\mathbf{k}} \end{bmatrix} + \begin{bmatrix} u_a \\ u_c \\ u_d \end{bmatrix}$$

Or

$$\mathbf{\Gamma} \begin{bmatrix} \ln a \\ \ln c \\ \ln d \end{bmatrix} = \begin{bmatrix} \mathbf{B}_{\mathbf{a}} \\ \mathbf{B}_{\mathbf{c}} \\ \mathbf{B}_{\mathbf{d}} \end{bmatrix} \ln \mathbf{Z} + \begin{bmatrix} u_a \\ u_c \\ u_d \end{bmatrix} \tag{24}$$

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

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

$$
\begin{cases}
\ln a = \mathbf{\Gamma}^{-1}\mathbf{B}_{\mathbf{a}} \ln \mathbf{Z} + \mathbf{\Gamma}^{-1} u_a \\
\quad = \Pi_a(\mathbf{q}) \ln \mathbf{Z} + \nu_a \\
\\
\ln c = \mathbf{\Gamma}^{-1}\mathbf{B}_{\mathbf{c}} \ln \mathbf{Z} + \mathbf{\Gamma}^{-1} u_c \\
\quad = \Pi_c(\mathbf{q}) \ln \mathbf{Z} + \nu_c \\
\\
\ln d = \mathbf{\Gamma}^{-1}\mathbf{B}_{\mathbf{d}} \ln \mathbf{Z} + \mathbf{\Gamma}^{-1} u_d \\
\quad = \Pi_d(\mathbf{q}) \ln \mathbf{Z} + \nu_d
\end{cases}
\tag{25}
$$

Where $\nu_i \sim N(0, \mathbf{\Sigma(q)})$ and $\mathbf{\Sigma(q)} = \Gamma^{\mathbf{-1}}\mathbf{\Psi}\Gamma$ (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 $\ln \mathrm{a} = l_a$, $\ln \mathrm{c} = l_c$, $\ln d = l_d$. Such observation contributes a function L_1 to the total log-likelihood function such that

$$
\begin{aligned}
L_1 &= P(\ln a = l_a) \times P(\ln c = l_c) \times P(\ln d = l_d) \\
&= P(\nu_a < -\Pi_a(q) \ln \mathbf{Z}) \times P(\nu_c < -\Pi_c(q) \ln \mathbf{Z}) \times P(\nu_d < -\Pi_d(q) \ln \mathbf{Z}) \\
&= \int_{-\infty}^{-\Pi_a(q)\ln \mathbf{Z}} \int_{-\infty}^{-\Pi_c(q)\ln \mathbf{Z}} \int_{-\infty}^{-\Pi_d(q)\ln \mathbf{Z}} \phi(\nu_a, \nu_c, \nu_d)\, d\nu_a\, d\nu_c\, d\nu_d
\end{aligned}
$$

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:

$$L_2 = \int_{-\infty}^{-\Pi_a(q)\ln \mathbf{Z}} \phi(v_a, \ln c - \Pi_c(q)\ln \mathbf{Z}, \ln d - \Pi_d(q)\ln \mathbf{Z}) dv_a \quad \text{for} \quad \ln a = l_a,\ \ln c = \ln c^o > l_c,\ \ln d = \ln d^o > l_d$$

$$L_3 = \int_{-\infty}^{-\Pi_c(q)\ln \mathbf{Z}} \phi(\ln a - \Pi_a(q)\ln \mathbf{Z}, v_c, \ln d - \Pi_d(q)\ln \mathbf{Z}) dv_c \quad \text{for} \quad \ln a = \ln a^o > l_a,\ \ln c = l_c,\ \ln d = \ln d^o > l_d$$

$$L_4 = \int_{-\infty}^{-\Pi_d(q)\ln \mathbf{Z}} \phi(\ln a - \Pi_a(q)\ln \mathbf{Z}, \ln c - \Pi_c(q)\ln \mathbf{Z}, v_d) dv_d \quad \text{for} \quad \ln a = \ln a^o > l_a,\ \ln c = \ln c^o > l_c,\ \ln d = l_d$$

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

$$L_5 = \int_{-\infty}^{-\Pi_a(q)\ln \mathbf{Z}} \int_{-\infty}^{-\Pi_c(q)\ln \mathbf{Z}} \phi(v_a, v_c, \ln d - \Pi_d(q)\ln \mathbf{Z}) dv_c\, dv_a \quad \text{for} \quad \ln a = l_a,\ \ln c = l_c,\ \ln d = \ln d^o > l_d$$

$$L_6 = \int_{-\infty}^{-\Pi_a(q)\ln \mathbf{Z}} \int_{-\infty}^{-\Pi_d(q)\ln \mathbf{Z}} \phi(v_a, \ln c - \Pi_c(q)\ln \mathbf{Z}, v_d) dv_d\, dv_a \quad \text{for} \quad \ln a = l_a,\ \ln c = \ln c^o > l_c,\ \ln d = l_d$$

$$L_7 = \int_{-\infty}^{-\Pi_c(q)\ln \mathbf{Z}} \int_{-\infty}^{-\Pi_d(q)\ln \mathbf{Z}} \phi(\ln a - \Pi_a(q)\ln \mathbf{Z}, v_c, v_d) dv_d\, dv_c \quad \text{for} \quad \ln a = \ln a^o > l_a,\ \ln c = l_c,\ \ln d = l_d$$

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

$$L_8 = \phi(\ln a - \Pi_a(q)\ln \mathbf{Z}, \ln c - \Pi_c(q)\ln \mathbf{Z}, \ln d - \Pi_d(q)\ln \mathbf{Z})$$

The total log-likelihood function for the system is therefore:

$$\begin{aligned} \log L = & \sum_{\ln a = l_a, \ln c = l_c, \ln d = l_d} \log L_1 + \sum_{\ln a = l_a, \ln c > l_c, \ln d > l_d} \log L_2 + \sum_{\ln a > l_a, \ln c = l_c, \ln d > l_d} \log L_3 + \sum_{\ln a > l_a, \ln c > l_c, \ln d = l_d} \log L_4 \\ & + \sum_{\ln a = l_a, \ln c = l_c, \ln d > l_d} \log L_5 + \sum_{\ln a = l_a, \ln c > l_c, \ln d = l_d} \log L_6 + \sum_{\ln a > l_a, \ln c = l_c, \ln d = l_d} \log L_7 + \sum_{\ln a > l_a, \ln c > l_c, \ln d > l_d} \log L_8 \end{aligned} \tag{27}$$

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, 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 below.

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 standards 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)[8]. Specifically, let $\hat{\Pi}$ (intercept, slope); and the diagonal elements of $\hat{\Sigma}$ (variances) be the first stage parameter estimates; and let the off diagonal elements of $\hat{\Sigma}$ (correlations) be the second stage estimates. The estimation procedure is as follows:

[8] For a detailed discussion of the Minimum distance estimator, the reader is referred to Ferguson (1958) Rothenberg (1973)

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 $\hat{\kappa} = \left[\hat{\Pi}, \hat{\Sigma}\right]$. Similarly, reduced form regression coefficients and covariance matrix are written as a function of structural parameters Π (q) and Σ(q) (as previously defined in relations [25-26]) and stacked in a vector $\kappa(\mathbf{q}) = \left[\Pi(\mathbf{q}), \Sigma(\mathbf{q})\right]$. 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 $\kappa(\mathbf{q})$:

$$Min_{\mathbf{q}} F(\mathbf{q}) = \{\hat{\kappa} - \kappa(\mathbf{q})\} \mathbf{W}^{-1} \{\hat{\kappa} - \kappa(\mathbf{q})\}'$$

Where **W** is a diagonal weight matrix with its diagonal elements equal to the estimated variances of $\hat{\kappa}$ (Muthén, 1984).

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

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

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).[9]

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 $\mathbf{Y} = [a,\ c,\ d]$ be the vector of choice variables, $\mathbf{Z}$ the vector of dependent variables.

Denoting by **Φ(.)** the normal CDF, marginal effects for the parameters in double-log are computed based on the following formula:

$$\frac{\partial\, E[\boldsymbol{Y}|\boldsymbol{Z}]}{\partial\, \boldsymbol{Z}} = \hat{\boldsymbol{q}}\, \boldsymbol{\Phi}\left(\frac{\hat{\boldsymbol{q}}\, \boldsymbol{Z}}{\sigma}\right)\frac{\overline{\boldsymbol{Y}}}{\overline{\boldsymbol{Z}}} \tag{28}$$

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

$$\frac{\partial\, E[\boldsymbol{Y}|\boldsymbol{Z}]}{\partial\, \boldsymbol{Z}} = \hat{\boldsymbol{q}}\, \boldsymbol{\Phi}\left(\frac{\hat{\boldsymbol{q}}\, \boldsymbol{Z}}{\sigma}\right)\overline{\boldsymbol{Y}} \tag{29}$$

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 $\hat{q}$:

---

[9] For W=V, the problem is to choose the Weighted Least Squares (WLS) estimator $\hat{\mathbf{q}}_{WLS}$ to minimize the WLS function $\mathbf{F}_{\mathbf{q}_{WLS}}$. Letting $\hat{\kappa}$ be the vector of parameters to estimate, the variance for this estimator is such that $Var\ (\hat{\mathbf{q}}_{WLS}) = n^{-1}\left[\Delta'\mathbf{V}\ \Delta\right]^{-1}$ where V is the asymptotic covariance matrix for $\hat{\kappa}$.

$$\hat{d} = \mathrm{Exp}[\hat{q} - \tfrac{1}{2}\hat{V}(\hat{q}) - 1] \tag{30}$$

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:

$$\frac{\partial\ E\ [\boldsymbol{Y}|\boldsymbol{Z}]}{\partial\ \boldsymbol{Z}} = \hat{\boldsymbol{d}}\ \boldsymbol{\Phi}\left(\frac{\hat{\boldsymbol{d}}\ \boldsymbol{Z}}{\sigma}\right)\ \bar{\boldsymbol{Y}} \tag{31}$$

The final estimated structural model is specified as:

$$\begin{cases} \ln a^o = \alpha_{a1} + \beta_{a1}\ln PDSI + \beta_{a2}\ln lagPDSI + \beta_{a3}\ln DL + \beta_{a4}\ln DLsq + \beta_{a5}\ln FILhat \\ \qquad + \beta_{a6}\ln SLOP + \beta_{a7}\ln ELEV + \beta_{a8}year87 + \beta_{a9}R_i + u_a \\ \\ \ln c^o = \alpha_{c1} + \delta_c \ln a^o + \beta_{c1}\ln PRESUP + \beta_{c2}\ln POPden + \beta_{c3}AN + \beta_{c4}AS + \beta_{c5}\ln DL + \beta_{c6}\ln DLsq \\ \qquad + \beta_{c7}\ln FILhat + \beta_{c8}\ln PRCP + \beta_{c9}\ln TMAX + \beta_{c10}\ln SLOP + \beta_{c11}\ln ELEV + \beta_{c12}R_i + \beta_{c13}year87 + u_c \\ \\ \ln d^o = \alpha_{d1} + \delta_{d1}\ln a^o + \delta_{d2}\ln c^o + \beta_{d1}AN + \beta_{d2}AS + \beta_{d3}\ln DL + \beta_{d4}\ln DLsq + \beta_{d5}\ln FILhat \\ \qquad + \beta_{d6}\ln PRCP + \beta_{d7}\ln TMAX + \beta_{d8}\ln SLOP + \beta_{d9}\ln ELEV + \beta_{d10}R_i + \beta_{d11}yeard + u_d \end{cases}$$

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. [10] 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 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

[10] 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.

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 *($\partial w/\partial a$)*, which amounts to \$4.87. [11]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 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

---

[11] In table 2-3, $\frac{\partial c}{\partial a}$ =\$4.81. We find marginal effect of acreage increase on per acre suppression costs as follows: $\frac{\partial w}{\partial a} = \left(\frac{\partial c}{\partial a} - \frac{\bar{c}}{\bar{a}}\right)\frac{1}{\bar{a}}$ where $\bar{a}$ and $\bar{c}$ are the mean values for acreage and costs reported in table 2-1.

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 = 307452)

Variable	Mean	Std. Dev.	Min	Max
Population density	63.9457	261.6049	0.17937	3496.198
Resource damage	245.34	12585.17	0 *	2491128
Suppression cost	182.279	5850.343	0 *	1212722
Acres burned	54.013	1817.981	0.1	499945
Pre-suppression cost	133.369	120.2905	0 *	1579.071
Aspect north	0.34808	0.476362	0 *	1
Aspect south	0.41453	0.492642	0 *	1
Slope	23.2778	23.67368	0 *	150
Elevation	4757.38	2733.28	0 *	88000
Delay	0.02707	0.541472	5 *	273.9583
Maximum Temperature	82.9971	11.47739	9.30882	109.0496

* Changed to 0.0001 to allow for log transformation used in the model estimation

Table 2-2: Data Description

Variables	**Description**
DAMAGE (lnD)	USFS estimate of Resource Damage. Generally includes only market value of timber and a crude estimate of recreation value (base year 2000)
COST *(lnC)*	Suppression cost, (base year 2000)
ACREAGE *(lnA)*	Total area burned per fire (acres)
PRE-SUPPRESSION *(lnPRESUP)*	Pre-Suppression costs (base year 2000)
POPULATION DENSITY *(lnPOPden)*	Population per square miles
FIRE INTENSITY LEVEL *(lnFILHAT)*	Fire intensity level (estimated value)
ASPECT *(AS, AN)*	Aspect at ignition (defined as a dummy): 1 if facing south (AS), 0 if not (AN)

Table 2-3: WLSMV Estimation results

	Equation 1 Dependent = LN (ACRES)			Equation 2 Dependent = LN (COST)			Equation 3 Dependent = LN (DAMAGE)		
Variable	Coefficient	Confidence interval	Marginal effect	Coefficient	Confidence interval	Marginal effect	Coefficient	Confidence interval	Marginal effect
INTERCEPT	------	------	------	------	------	------	------	------	------
LN (ACRES)	------	------	------	-1.737* (0.295)	[-2.315; -1.159]	-4.81	2.853* (0.165)	[2.53; 3.177]	1.76
LN (COST)	------	------	------	------	------	------	-0.663* (0.021)	[-0.704;-0.622]	-0.12
YEAR1	1.592* (0.018)	[1.556; 1.628]	3.91	7.875* (0.472)	[6.951; 8.799]	2629	------	------	------
LN (PPDSI)	-0.018	[-0.097; 0.061]	-0.04	------	------	------	------	------	------

Note: Standard errors are in parenthesis

*   Significant at 1%
** Significant at 10%

Figure 2-1: C+NVC model (Donovan and Rideout, 2003)

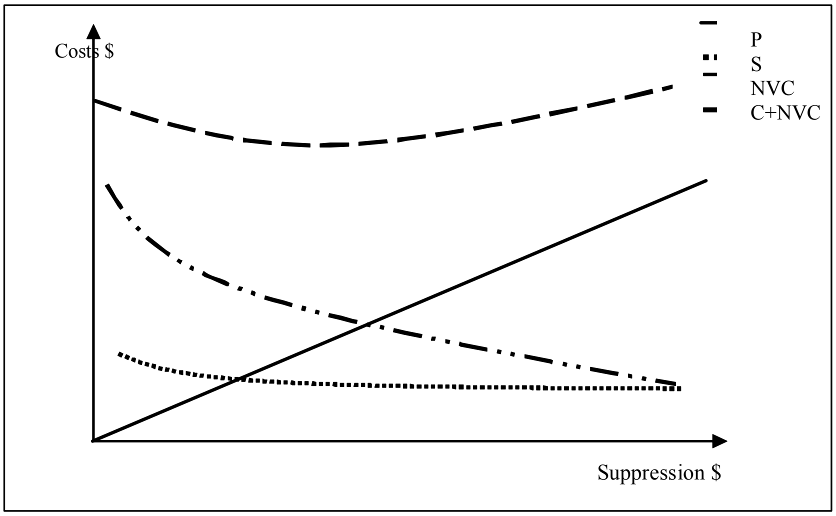
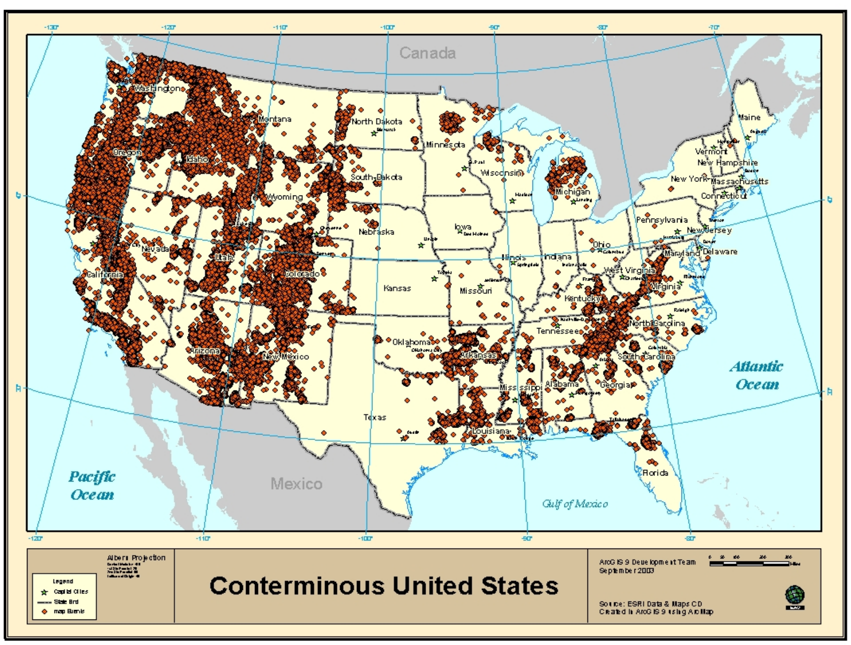


Figure 2-2: Distribution of wildfires in the U.S. 1970-2002



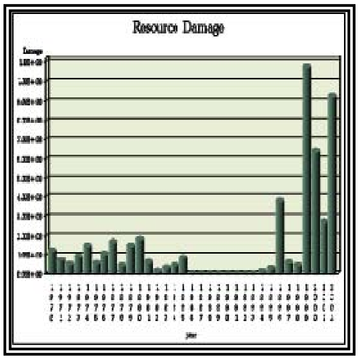
Number of fires

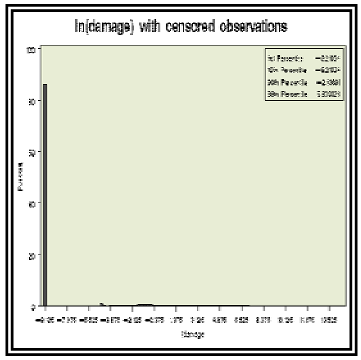
Total = 307452

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





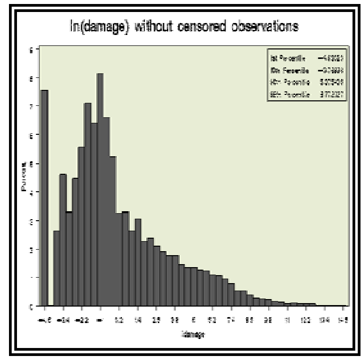
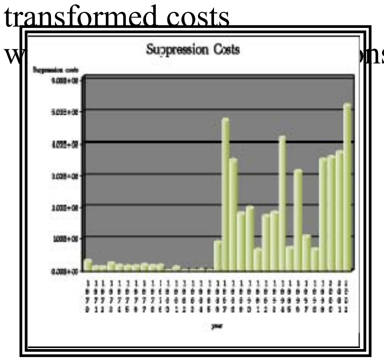
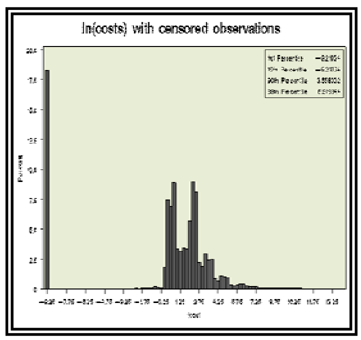


Figure 2-6: Suppression costs **Figure 2-7:** log- transformed costs **Figure 2-8**: log-transformed costs w ns





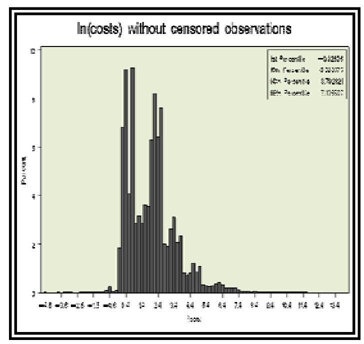
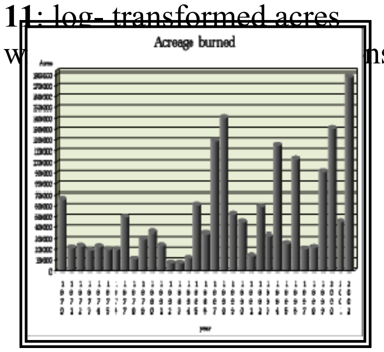
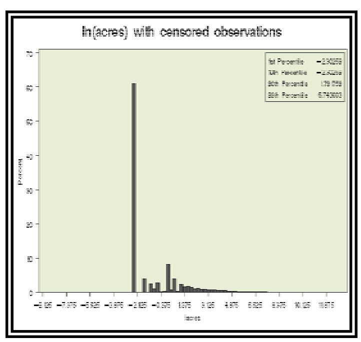


Figure 2-9: Total acres burned **Figure 2-10:** log- transformed acres **Figure 2-11**: log- transformed acres w ns





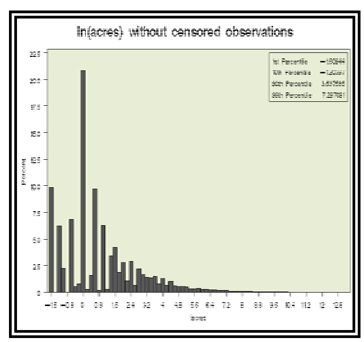
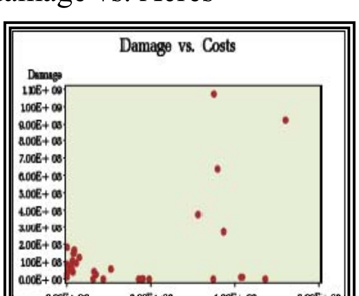
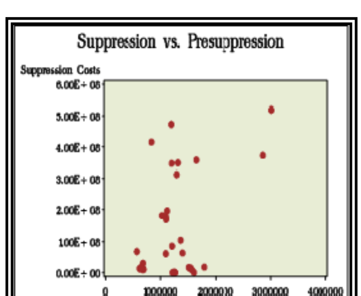
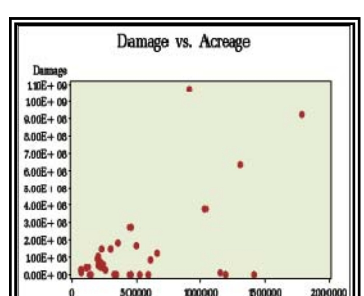


Figure 2-12: Scatter plot of Resource damage vs. Costs **Figure 2-13:** Scatter plot of Suppression vs. Pre-suppression **Figure 2-14:** Scatter plot of Resource damage vs. Acres







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