ESTIMATING THE EFFICACY OF FIGHTING FIRE: PROPENSITY SCORE AND INSTRUMENTAL VARIABLE METHODS

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ABSTRACT

In this paper we estimate the treatment effects wildfire suppression (fire crew response time) and fuel management (prescribed fire) have on wildfire size and intensity. Since wildfire management (suppression and fuel management) is likely endogenous to wildfire behavior, we develop instrumental variables (IV) and propensity score matching (PSM) methods to provide consistent estimations of the returns to management. The suitability of IV versus PSM methods depends largely on the assumptions made and the data available, and in the case of wildfire modeling, it seems PSM may be more appropriate. While the vast majority of PSM literature focuses on binary treatments, we explore the ability of recently developed continuous treatment propensity score models. We find that in general wildfire management does limit wildfire size and intensity. However, our results differ depending on the estimation strategy (OLS, IV, PSM) employed.

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I. INTRODUCTION

Nationwide wildfires burn over 4 million acres annually (1960-2004), costing Federal agencies over $830 million per year (1994-2004) in suppression costs alone (National Interagency Fire Center 2005). Is this enough or not?—are we over, under, or optimally funding wildfire suppression activities? How about fuel management activities (for example, prescribed burning)? These are difficult questions to answer when we have little information on the damages and benefits associated with wildland fire[1]. If marginal net benefits (damages *avoided* net of costs of fires) exceed those marginal expenditures mitigating fire, then it is clear wildfire suppression and fuel management programs are under-funded. Of course, the opposite might hold true.

The idea of an "optimal wildfire size" has been around since Sparhawk introduced it in 1925. He explains that the optimal size is one which yields the minimum 'cost plus loss' (cost of wildland management—suppression and fuel treatment—plus loss due to wildfire damage). This is an important result, as it may justify in some instances, "let burn" or limited-action (no or limited suppression) strategies—when the wildfire damages pale in comparison to the cost of treatment/mitigation. Rideout and Omi (1990) formalize innovations instituted into the least-cost model by Gorte and Gorte (1979) and Davis (1965), who contend that optimal wildfire size is that which corresponds with the minimum cost plus *net value change* (NVC—damages net of benefits), as a profit maximization type problem. The goal is to maximize the value of wildfire avoidance given the costs of production inputs, such as wildfire management—suppression and fuel management.

Conceptually, the value of wildfire avoidance is the price of damage averted times the amount of wildfire averted. The problem is we do not observe wildfire averted. We observe the fact a fire occurred, that it was of a particular size, severity, and/or intensity, and perhaps that some resources were used to mitigate it, but we do not observe the size *it would have been* had there not been a fire suppression crew or any prior fuels management. We can model observed wildfire as a function of wildfire management, and other variables, and through such a model we

[1] Few studies have examined the damages of wildfire, Butry et al. 2001 provides an example using the 1998 Florida wildfires.

can quantify how management averts wildfire. However, as we will discuss in the next few sections, wildfire management may be endogenous to wildfire behavior, so OLS estimation of the wildfire production equation will be biased and inconsistent.

Much of the previous empirical wildfire research has focused on either modeling the probability of a wildfire occurrence (ignition) or modeling wildfire size (or severity). The former research primarily examines the factors involved in the probability of fire ignition (fire risk modeling), while the latter research examines the factors contributing to a fire's final size or degree of severity. In general, previous empirical research finds that wildfire behavior (however defined—whether meaning frequency, occurrence, size, or severity) to be generally related to four sets of factors, which include wildfire specific characteristics, climate and weather conditions, wildfire management and mitigation (including prescribed fire and suppression/initial attack effort), and landscape attributes (including dominant landuse/landcover characteristics and socioeconomic characteristics) (see Butry, Gumpertz, and Genton for a review). However, only recently has modeling made explicit the endogeneity of wildfire management to fire (Yoder).

In Sections II, III, and IV we examine the role endogeneity plays in the statistical modeling of wildfire behavior and how, in theoretical terms, instrumental variables (IV) and propensity score matching (PSM) techniques can be used to address the endogeneity issue. Section V applies the OLS, IV, and PSM in an empirical application where we model wildfire size and intensity as a function, among other things, of wildfire management. Finally, Section VI presents our findings and offer some future research directions.

II. ENDOGENEITY

In modeling wildfire there are two sources of potential endogeneity—simultaneity bias and sample selection bias. Simultaneity occurs when two or more variables are co-determined with each other. Statistical bias results, in a least-squares framework, if we regress one of the endogenous variable on any others. It is easy to imagine why wildfire behavior and suppression effort may be simultaneously determined—initial wildfire behavior influences the fire crew effort and response, but in turn, fire crew effort affects wildfire behavior. Using least squares in this instance leads to biased estimates. In fact, we would expect OLS to underestimate suppression's effectiveness.

Selection bias occurs when observations are non-randomly selected[2] into a group and we are interested in how the group inclusion affects some outcome, but we ignore the fact that those factors causing group participation also directly affect the outcome. Prescribed burning typically occurs in winter and early spring in advance of the wildfire season, so problems of endogeneity due to simultaneity are largely absent. However, because prescribed burning occurs in areas chosen by wildland managers, the selection of prescribed burn sites are not determined by a random process. In fact we would expect prescribed burning to be applied to areas with higher wildfire risk, implying that areas with prescribed burning may be different than those without.

Suppose the wildfire system is composed of three equations where suppression and wildfire are simultaneously determined and prescribed fire is defined by a non-random selection process:

(wildfire) $$w_i = \beta_0 + \beta_1 c_i + \beta_2 s_i + \beta_3 p_i + \beta_4 y_i + \varepsilon_i \tag{2.1}$$

(suppression) $$s_i = \alpha_0 + \alpha_1 c_i + \alpha_2 x_i + \alpha_3 w_i + v_i \tag{2.2}$$

(prescribed fire) $$\begin{aligned} p_i^* &= \delta_0 + \delta_1 c_i + \delta_2 z_i + u_i \\ p_i &= p_i^* \text{ if } p_i^* > 0 \\ p_i &= 0 \text{ if } p_i^* \le 0 \end{aligned} \tag{2.3}$$

where *w* is wildfire, *s* is suppression, *p* is prescribed fire (p^* is a latent variable), *c*, *y*, *x*, and *z* are all exogenous variables (and uncorrelated with ε, *v*, and *u*), the β's, α's, and δ's are parameters, and ε, *v*, and *u* are error terms with zero means and

[2] This can occur if individuals self-select themselves in, or if the program administrator selects individuals based on some attributes.

$$Cov(\varepsilon, v, u) = \begin{bmatrix} \sigma_{\varepsilon}^2 & 0 & \rho_{\varepsilon u} \\ 0 & \sigma_v^2 & 0 \\ \rho_{u\varepsilon} & 0 & \sigma_u^2 \end{bmatrix}$$

In this system the error terms for prescribed fire and wildfire are correlated due to unobservables that influences both selection process and wildfire behavior and we are assuming that ε_i and v_i are uncorrelated.

Again, we are interested in evaluating the effectiveness of wildfire suppression and prescribed fire on wildfire behavior, however given the endogeneity exhibited between wildfire management (suppression and prescribed fire) and wildfire, OLS estimation of (2.1) will yield biased treatment effect estimates (β_2 and β_3). Below we will examine methods for correcting endogeneity in both its forms, with the focus on the use instrumental variables (IV) then introduce a relatively new approach, propensity score matching (PSM).

A note about language—*treatment* (suppression and prescribed fire) is what is applied to the outcome (wildfire). We are interested in the treatment effect on outcome.

Selection & Prescribed Fire

The correlated error terms u and ε, imply that variables that influence both prescribed fire and wildfire are unobservable to the analyst, so that OLS estimation of (2.1) yields biased and inconsistent prescribed fire effect estimate ($E[\varepsilon \mid p] \neq 0$) as

$$Cov[p, \varepsilon] = Cov[u_i \varepsilon_i] = \rho_{\varepsilon u} \neq 0$$

Simultaneity & Suppression

We see that OLS estimation of (2.1) will yield biased and inconsistent model parameters, since, $E[\varepsilon \mid s] \neq 0$, as

$$Cov[s,\varepsilon] = \frac{\alpha_3\beta_3\rho_{\varepsilon u} + \alpha_3\sigma_\varepsilon^2}{(1-\alpha_3\beta_2)} \neq 0$$

where the reduced form of *s* is:

$$s_i = \frac{\alpha_0 + \alpha_3\beta_0 + (\alpha_1 + \alpha_3\beta_1)c_i + \alpha_2 x_i + \alpha_3\beta_3 p_i + \alpha_3\beta_4 y_i + \alpha_3\varepsilon_i + v_i}{(1-\alpha_3\beta_2)} \tag{2.4}$$

III. INSTRUMENTAL VARIABLES & ENDOGENEITY

Two standard modeling methods exist in dealing with the selection issue—selection models and instrumental variables models—while instrumental variables is usually employed with simultaneity. Selection models were designed to accommodate endogenous treatment variables, however the predominance of work involves binary treatment variables (rather than continuous or semi-continuous), and work by employing an additional structure to (2.1) to correct (control) for the non-zero conditional expectation of the error given the endogenous variable(s). However, our wildfire system does not include a binary treatment variable, at least at the scale of our model. The IV method essentially replaces the endogenous variable with a instrument variable that is highly correlated with the endogenous explanatory variable, but that is not correlated with the error term, so the covariance between the instrument and the error term is zero. This method is general enough to instrument endogenous variables stemming from both continuous (we will assume suppression is continuous) and semi-continuous (we will assume some places, but not all, received prescribed fire and the amount varies by location) distributions.

IV Framework

Putting aside the wildfire system for the moment, we present how IV works using the following model:

$$\mathbf{y} = \mathbf{XB} + \mathbf{e} \tag{3.1}$$

where $\mathbf{y}$ is a Nx1 vector of the dependent variable, $\mathbf{X}$ is a NxK matrix of explanatory variables where J variables are endogenous ($J \le K$), $\mathbf{B}$ is a Kx1 vector of parameters, and $\mathbf{e}$ is an Nx1 error term. Ordinary least-squares estimation of (3.1) yields:

$$\hat{\mathbf{B}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} \tag{3.2}$$

which we know is biased as E[$\mathbf{e}$ | $\mathbf{X}$] ≠ 0 (since $\mathbf{X}$ contains J endogenous variables). However let us assume a set of variables exist, $\mathbf{Z}$, where

$$\begin{aligned} &\text{plim}\left(\frac{1}{N}\mathbf{Z}'\mathbf{e}\right) = 0 \\ &\text{plim}\left(\frac{1}{N}\mathbf{Z}'\mathbf{X}\right) \text{ exists and is nonsingular} \\ &\text{plim}\left(\frac{1}{N}\mathbf{Z}'\mathbf{Z}\right) \text{ exists and is nonsingular} \end{aligned} \tag{3.3}$$

If the above conditions hold then $\mathbf{Z}$ instruments $\mathbf{X}$ and we can estimate $\mathbf{B}$ consistently. The first condition above states our requirement that the instruments be orthogonal to the error term. The second and third conditions require the matrix products to be invertible, which will not happen unless a identification condition is satisfied—each instrument that replaces the J endogenous variables must be nonlinear combinations of any of the other variables, otherwise we will not be able to identify the effect $\mathbf{x}_k$ has on $\mathbf{y}$.

If $\mathbf{Z}$ exists then consistent estimation of $\mathbf{B}$ can be achieved, as:

$$\begin{aligned} &\mathbf{Z}'\mathbf{y} = \mathbf{Z}'\mathbf{X}\mathbf{B} + \mathbf{Z}'\mathbf{e} \\ \text{so then,}\quad &\hat{\mathbf{B}}_{IV} = (\mathbf{Z}'\mathbf{X})^{-1}\mathbf{Z}'\mathbf{y} \end{aligned} \tag{3.4}$$

As required, $\mathbf{Z}$ is orthogonal to $\mathbf{e}$ and $\mathbf{Z}$ and $\mathbf{X}$ are correlated, making the IV estimates consistent.

Two-Stage Least Squares (TSLS) Framework

If **Z** is *N*x*K*, then (*K*-*J*) exogenous variables in **X** serve as their own instrument in **Z** (they are perfectly correlated with themselves and not correlated with the error term), but we replace the *J* endogenous variables with at least *J* instruments (different variables). Although, **Z** does not need to be *N*x*K*, but rather may be *N*x*L*, where *L*≥*K* (implying that we have more instruments than endogenous variables), the above framework, (3.3) & (3.4), will require modification since $\text{plim}\left(\frac{1}{N}\mathbf{Z}'\mathbf{X}\right)$ will not have an inverse. Multiplying the regression of **X** on **Z** by **X**, produces $\hat{\mathbf{X}}$, which will be *N*x*K*. Regressing **y** on $\hat{\mathbf{X}}$ yields consistent estimates[3] if $\text{plim}\left(\hat{\mathbf{X}}'\hat{\mathbf{X}}\right)$ has a inverse,

$$\hat{\mathbf{X}} = \mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{X}$$
$$\hat{\mathbf{B}}_{TSLS} = (\hat{\mathbf{X}}'\hat{\mathbf{X}})\hat{\mathbf{X}}'\mathbf{y} \qquad (3.5)$$

Asymptotic Variance-Covariance Matrix

The OLS estimated variance-covariance matrix of $\hat{\mathbf{B}}_{TSLS}$ does not equal the asymptotic variance-covariance matrix for $\hat{\mathbf{B}}_{TSLS}$, and for hypothesis testing we need to use the asymptotic standard errors. The asymptotic variance-covariate matrix equals (Greene):

$$\text{Asy.Var.}\hat{\mathbf{B}}_{TSLS} = \hat{\sigma}_e^2\left(\hat{\mathbf{X}}'\hat{\mathbf{X}}\right)^{-1}$$

where

$$\hat{\sigma}_e^2 = \left(\mathbf{y} - \mathbf{X}\hat{\mathbf{B}}_{TSLS}\right)\left(\mathbf{y} - \mathbf{X}\hat{\mathbf{B}}_{TSLS}\right)' \qquad (3.6)$$

[3] When **Z** is *N*x*K*, it can be shown that $\hat{\mathbf{B}}_{TSLS} = \hat{\mathbf{B}}_{IV}$.

Note that we are using **X** instead of $\hat{\mathbf{X}}$, which is used by OLS.

Instruments for Prescribed Fire

Examining (2.3) we see that two instruments exist, *c* and *z*, both affect prescribed fire, but are orthogonal to the wildfire equation error term, ε. Regressing *p* on *c* and *z* will allow for the construction of a good instrument for prescribed fire, although since *p* is defined by a censored normal distribution we can construct $\hat{p}$ using a censored regression (Tobit), as (see Maddala):

$$E[p_i] = \hat{p}_i = \Pr(p_i > 0) \cdot E[p_i \mid p_i > 0] + \Pr(p_i = 0) \cdot E[p_i \mid p_i = 0]$$

where,

$$E[p_i \mid p_i > 0] = E[\delta_0 + \delta_1 c_i + \delta_2 z_i + u_i \mid p_i > 0] = \delta_0 + \delta_1 c_i + \delta_2 z_i + E[u_i \mid p_i > 0]$$

$$= \delta_0 + \delta_1 c_i + \delta_2 z_i + E[u_i \mid u_i > -\delta_0 - \delta_1 c_i - \delta_2 z_i]$$

$$= \delta_0 + \delta_1 c_i + \delta_2 z_i + \sigma_u \frac{\phi\left(\dfrac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\hat{\sigma}_u}\right)}{\Phi\left(\dfrac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\hat{\sigma}_u}\right)}$$

(using the moments of a truncated normal distribution).

$$E[p_i \mid p_i = 0] = 0$$

so that,

$$E[p_i] = \hat{p}_i = \Pr(p_i > 0) \cdot E[p_i \mid p_i > 0] + \Pr(p_i = 0) \cdot E[p_i \mid p_i = 0]$$

$$= \Phi\left(\frac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\sigma_u}\right)\left(\delta_0 + \delta_1 c_i + \delta_2 z_i + \sigma_u \frac{\phi\left(\frac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\sigma_u}\right)}{\Phi\left(\frac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\sigma_u}\right)}\right)$$

where ϕ and Φ are the standard normal pdf and cdf, respectively.

Two-stage estimation of the Tobit model requires that we first estimate $\Pr(p_i \mid p_i > 0)$ using a probit model to get estimates of $\frac{\delta_0}{\sigma_u}$, $\frac{\delta_1 c_i}{\sigma_u}$, and $\frac{\delta_2 z_i}{\sigma_u}$, in order to calculate $\hat{\phi}_{\text{Probit}}\left(\frac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\sigma_u}\right)$ and $\hat{\Phi}_{\text{Probit}}\left(\frac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\sigma_u}\right)$ (the 'probit' subscript denotes that the calculation is based on the probit model estimates) and in order to estimate $E[p_i \mid p_i > 0]$ using OLS as

$$E[p_i \mid p_i > 0] = \delta_0 + \delta_1 c_i + \delta_2 z_i + \sigma_u \frac{\hat{\phi}_{\text{Probit}}\left(\frac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\sigma_u}\right)}{\hat{\Phi}_{\text{Probit}}\left(\frac{\delta_0 + \delta_1 c_i + \delta_2 z_i}{\sigma_u}\right)}$$

where ϕ_i/Φ_i enters as an additional model regressor. OLS will yield consistent estimates of the δ's and σ_u (the ones outside the ϕ and Φ terms).

Instruments for Suppression

Since suppression is a function of wildfire, we solve for the reduced form suppression equation, (2.4), to determine appropriate instruments—*c*, *x*, *p*, and *y*. Since *p* is correlated with the ε it cannot be included as an instrument, although the instrument for it, $\hat{p}$, can. Regressing *s* on *c*, *x*, $\hat{p}$, and *y* allows for construction of an instrument for *s*:

$$E[s_i] = \hat{s}_i = E[\pi_0 + \pi_1 c_i + \pi_2 x_i + \pi_3 \hat{p}_i + \pi_4 y_i + \zeta_i]$$

$$= \pi_0 + \pi_1 c_i + \pi_2 x_i + \pi_3 \hat{p}_i + \pi_4 y_i$$

where the π's are estimated using OLS and $\zeta \sim N[0,1]$.

Instrumental Variable Estimation of Wildfire

We can now estimate (2.1) using OLS with instruments $\hat{s}$ and $\hat{p}$ as

$$w_i = \beta_0 + \beta_1 c_i + \beta_2 \hat{s}_i + \beta_3 \hat{p}_i + \beta_4 y_i + \xi_i$$

where $\xi \sim N[0,\sigma_\xi^2]$ and is uncorrelated with $\hat{s}$ and $\hat{p}$, since

$$Cov[\hat{p}_i,\xi_i] = E[\hat{p}_i\xi_i] = \hat{\Phi}_{\text{Probit}}\left(\frac{\delta_0+\delta_1 c_i+\delta_2 z_i}{\sigma_u}\right)\left(\hat{\delta}_0 + \hat{\delta}_1 c_i\xi_i + \hat{\delta}_2 z_i\xi_i + \hat{\sigma}_u \frac{\xi_i \hat{\phi}_{\text{Probit}}\left(\frac{\delta_0+\delta_1 c_i+\delta_2 z_i}{\sigma_u}\right)}{\hat{\Phi}_{\text{Probit}}\left(\frac{\delta_0+\delta_1 c_i+\delta_2 z_i}{\sigma_u}\right)}\right) = 0$$

and

$$Cov[\hat{s}_i,\xi_i] = E[\hat{s}_i\xi_i] = \hat{\pi}_0\xi_i + \hat{\pi}_1 c_i\xi_i + \hat{\pi}_2 x_i\xi_i + \hat{\pi}_3 \hat{p}_i\xi_i + \hat{\pi}_4 y_i\xi_i + \zeta_i\xi_i = 0$$

where "^" over the δ's and π's denotes the OLS estimates.

However, the OLS generated standard errors of the coefficients will be incorrect, as noted in the previous section. The OLS generated standard error is

$$\hat{\sigma}_\xi^2 = \left(\sum\left(w_i - \hat{\beta}_0 + \hat{\beta}_1 c_i - \hat{\beta}_2 \hat{s}_i - \hat{\beta}_3 \hat{p}_i - \hat{\beta}_4 y_i\right)^2\right)^{1/2}$$

The standard error should be based on the error in (2.1), so that the asymptotic standard errors for the instrumented treatment variables are:

$$\text{Asy.}\,\hat{\beta}_{SE_k} = \frac{\hat{\sigma}_{\varepsilon}}{\hat{\sigma}_{\xi}}\hat{\beta}_{SE_k}$$

where,

$$\hat{\sigma}_{\varepsilon} = \left(\sum_{i=1}^{n}\left(w_i - \hat{\beta}_0 + \hat{\beta}_1 c_i - \hat{\beta}_2 s_i - \hat{\beta}_3 p_i - \hat{\beta}_4 y_i\right)^2\right)^{1/2}$$

TSLS regression of the wildfire equation will produce consistent treatment effect estimates of suppression and prescribed fire on wildfire behavior, given good instruments.

IV. PROPENSITY SCORE MATCHING & ENDOGENEITY

Instrumental variables allows for consistent estimation of the endogenous variable, but requires several conditions to be met in order to do so. IV requires the existence of instruments that are closely related to the endogenous variables (the higher the correlation the better the estimate; with weak correlations OLS may be less biased than IV (Bound, Jaeger, and Baker)), but at the same time, uncorrelated with the error term; IV requires an identification condition to be met—for each endogenous variable there must be at least one instrument that does not directly affect the outcome variable; IV is a parametric modeling approaches, so it requires a specification of a function form and even minor misspecification has been shown severely bias estimates (Bartels).

Propensity score matching (PSM) is a technique used to estimate treatment effects (evaluate programs) when treatment is endogenous to the outcome. The overwhelming majority of PSM literature involves a binary treatment and is applied in labor economics and in epidemiological studies (See Rosenbaum and Rubin 1983; Smith and Todd; Heckman and Hotz, Dehejia and Wahba for an detailed introduction). PSM works by comparing the outcome of treated observations with their untreated counterparts, but the comparison is directed by a matching technique. We match and compare treated and untreated observations based on a like probability to be treated.

The intuition behind PSM is straightforward. Suppose there are two groups—a treated group and an untreated group—and those that participated in treatment chose to do so because of some factor *x*, and where the probability of participation is a positive function of *x*. Researchers are interested in quantifying any enhancement the treatment has on some outcome. However, further suppose that outcome is also a positive function of *x*, hence OLS estimation of outcome on treatment would be biased due to selection bias. If the researchers test their hypothesis by simply comparing the mean outcomes between the two groups, then they will mistakenly overvalue the enhancement treatment has on outcome, as in the absence of treatment, the average outcome for the participant group would be higher than the non-participants because of *x*. PSM works by matching treated with untreated observations based on their probability (propensity) of treatment, which would be modeled as a function of *x*. Thus those matched observations with the same propensity score would have the distribution of *x* regardless of treatment status, and so any difference between the treated and untreated observations could be attributed to the treatment. If *x* is univariate, then we can simply match on *x*, but the advantage of using PSM is when *x* is multivariate (eliminates the curse of dimensionality).

PSM differs from IV in that it requires the analyst to have information on all the factors that directly influence both treatment and the outcome (called 'selection on observables'), however unlike IV, PSM does not need to satisfy a identification condition. Actually the selection on observables is not even really required, as unobservables are OK, so long as alternative variables are available that share the same distribution as the unobserved ones (essentially instrumenting for the unobservables). PSM is semiparametric and has been found to be robust when the outcome is a nonlinear (LaLonde; Winship and Mare; Joffe and Rosenbaum; Rubin and Thomas; Imai and van Dyk).

While PSM has a number of advantages over IV, and certainly OLS, as mentioned the majority of research involves binary treatments. Below we will detail a propensity score with continuous treatment model then explain how it can be applied to the wildfire system above (we will still refer to the propensity score approach as ‘PSM’ even though in the continuous case we are not matching).

Propensity Scores and Continuous Treatment Variables

The majority of PSM literature focuses on a binary treatment decision (treat or no-treat) or multi-valued, ordinal treatment (for instance, see Behrman, Cheng, Todd), but very recent work allows for the propensity scores to be used with continuous treatment variables (Hirano and Imbens; Imai and van Dyk; Imbens; Lu, Zanutto, Hornik, and Rosenbaum).

In the binary treatment case, treated observations are matched with non-treated (control) observations based on their like propensity score (probability of treatment). The propensity score is estimated by regressing treatment status on *all*[4] covariates that affect *both* the treatment status and the outcome. The goal of propensity score matching is to balance the distribution of covariates that affect treatment and outcome between the two treatment groups (the balancing condition). Thus, matched pairs of treated and non-treated observations (matched based on their like propensity score) have the same distribution of covariates that affect treatment and outcome, so that any differences in their outcomes are causally attributed to the treatment. The balancing condition does not necessarily match treated observations with an untreated observation(s) sharing the exact same values of the covariates, rather it requires that within a propensity score subgroup (all observations, both treated and untreated observations, having similar propensity scores) that the distribution of the covariates between the treated and untreated observations are the same, so that, on average, the difference in outcomes between the treated and untreated, within that subgroup, are due to the treatment.

When treatment is a continuous variable, rather than binary, this implies that all of the observations received some treatment and only differ with respect to their level of treatment.

[4] Again, technically this does not need to hold. If one covariate that directly influences both treatment and outcome is unobserved, but another variables exists which shares the same distribution as the unobserved variable, across the treated and untreated group, then we can include this observed variable in place of the unobserved and PSM will be unbiased.

Unlike the binary case, we no longer have a control group to compare with the treated group, so the matching framework needs to be modified[5].

Let *T* be treatment (*T* may be multivariate), *y* be outcome after treatment, y^0 be outcome in the absence of treatment, *X* be a set of covariates, p{·} denote distribution.

If endogeneity exists, then

$$p\left\{y^0 \mid T = T^H\right\} \neq p\left\{y^0 \mid T = T^L\right\}$$

where $T^H \neq T^L$. If the distribution of outcome in the absence of treatment differs depending on the actual treatment applied, then differences in outcome is due to treatment and factors related to treatment. Endogeneity implies that T^H will be applied to different types of observations than those to receive T^L.

Assumptions

Stable Unit Treatment Value (Imai and van Dyk):

The distribution of expected outcome for observation i is independent of the expected treatment for j, for all i≠j, given covariates.

Strong Ignorability of Treatment Assignment Given Covariates (Imai and van Dyk):

$$p\left\{y^0 \mid X, T\right\} = p\left\{y^0 \mid X\right\}$$

The distribution of outcome in the absence of treatment is independent of treatment, given covariates.

[5] We could discretize our continuous treatment into several ordinal treatment groups. We could compare two ordinal groups using the propensity score matching framework to obtain the treatment effect of moving from the lower group to the higher group (see Behrman, Cheng, and Todd). Of course the boundaries for the groups may be rather arbitrary, and perhaps, meaningless. Also with continuous treatment, it may be more interesting (and meaningful) to examine the marginal effect of treatment.

Strong ignorability implies that if we condition on covariates, treatment is independent of outcome in the absence of treatment. Note that we are not saying treatment is independent of outcome, as we expect treatment to modify outcome, but rather we would expect observations with the same *X* to behave the same with the same level of treatment[6].

<u>Uniquely Parameterized Propensity Function</u> (Imai and van Dyk):

For every X, there exist some parameter, θ, (of lower dimension) where the density function, $e_\psi(\cdot \mid X)$, depends on X only through $\theta_\psi(X)$.

The parameter θ is the propensity score, $e_\psi(\cdot|X)$ is the propensity function, and ψ parameterizes the distribution of the propensity score estimator. The propensity score estimator is defined as

$$\theta_\psi(X) = E[T \mid X]$$

$$\psi = [\beta, \sigma^2]$$

Implications

<u>*The Propensity Function as a Balancing Score*</u> (Imai and van Dyk):

If the distribution of treatment conditioned on the propensity function does not depend on covariates, then the propensity function is a balancing score.

$$p\{T \mid X\} = p\{T \mid X, e_\psi(\cdot \mid X)\} = p\{T \mid e_\psi(\cdot \mid X)\}$$

<u>*Strong Ignorability of Treatment Assignment given the Propensity Function*</u> (Imai and van Dyk):

[6] In the binary case expected treatment, $E[T_i]$, takes on two values, 0 and 1. The strong ignorability assumption is the critical assumption in the binary case, as it is here. Actually, in the binary we only need to assume weak ignorability—that the outcome associated with no treatment is independent of the actual treatment, given covariates, or $y_i^0 \perp T_i \mid X$. This means that *conditional on the covariates,* the expected outcome of treated observations *if they had not been treated* is equal to the expected outcome of non-treated observations.

Strong ignorability in the binary case implies that the outcome associated with treatment is independent of the actual treatment, given covariates, *and* the outcome associated with no treatment is independent of the actual treatment, given covariates, or $(y_i, y_i^0) \perp T_i \mid X$. However it can be easily shown that we do not need strong ignorability to identify the average treatment effect in the binary case, but we do in the continuous case.

If the propensity function is a balancing score, then the distribution of outcome in the absence of treatment, conditioned on the propensity function, does not depend on treatment.

$$p\{y^0 \mid T, e_\psi(\cdot \mid X)\} = p\{y^0 \mid e_\psi(\cdot \mid X)\}$$

Since the propensity score uniquely indexes the propensity function for all values of *X*, then given the propensity score, there is strong ignorability of treatment assignment,

$$p\{y^0 \mid T, \theta\} = p\{y^0 \mid \theta\}$$

The distribution of expected outcome is independent of treatment, conditioned on the propensity score.

Treatment Effect

If there exists a propensity score that satisfies both the balancing and strong ignorability conditions, then if we model the conditional distribution of the outcome as a function of treatment, we should be able to identify the true treatment effect. In practical terms, the distribution of outcome is modeled using a parametric form while conditioning on the propensity score, which is also modeled parametrically. Imai and van Dyk estimate the propensity score, test for covariate balance, then group observations into propensity score strata and outcome is regressed, using OLS, on outcome and covariates (the covariates are included as it has been found to reduce bias). The weighted average treatment effect, across strata, becomes the average marginal treatment effect.

V. EMPIRICAL WILDFIRE MODEL

In this section we estimate the treatment effect of suppression and fuel management on wildfire behavior. Our suppression variable is fire crew response time, a measure of initial attack, or the time it takes a fire crew from wildfire discovery until arrival. Effective initial attack may be the difference between a contained wildfire and a larger uncontrolled one. Fuel management is used to minimize the risk of a damaging wildfire through elimination of understory and ladder fuels. Prescribed fire, herbicides, and mechanical treatments are common fuel management techniques, with prescribed fire being popular in Florida. Prescribed burning is applied in advance of the fire season and has been shown to have lasting effects up to about 3 years on very fine scale experimental plots (Outcalt and Wade). We examine the effect fire crew response time and prescribed fire has on two realizations of wildfire—fire size and flame length. We examine size and length because focusing on size alone may be misleading. Wildfires may be big, but not intense, thus not very damaging. For instance, prescribed fire, by limiting ladder fuels, may allow for larger wildfires (they may now move quicker through less dense forest), but of low intensity. If wildfire management (suppression and prescribed fire) minimizes the chance of crown fires, perhaps at the expense of surface area burned, this might be seen as a success. Flame length is used since it is highly correlated with wildfire intensity (Kennard) and it is more easily observed.

Dataset and Study Site

We examine the St. Johns River Water Management District (SJRWMD) in northeast Florida. The SJRWMD area comprises portions of the 18 northeast counties in Florida. The SJRWMD is an ideal study area given its abundance of wildfire (in size and occurrence), use of prescribed fire, values at risk (fires are potentially very damaging and are actively managed), and quality of available data. In fact, Florida in general is an interesting place of study for wildfires, however, the SJRWMD is chosen given familiarity from past research. Florida, unlike many areas of the western United States, is heavily populated (it is fourth in state population and ninth in population density) (US Census Bureau) and averages 218,638 wildfire acres a year and 763,205 acres of prescribed fire a year (476,590 is for hazard reduction)[7]. Between wildfire and silvicultural prescribed fire, approximately 3% of Florida burns annually. The SJRWMD averages over 48,596 acres a year in wildfire and 133,833 acres of prescribed burning (73,099 for hazard reduction).

Wildfire Records

Data on individual wildfire occurrences was obtained from the Florida Division of Forestry (FDOF). FDOF's wildfire data contains detailed information of fires found on private and state-

[7] This is silvicultural based prescribed burning. Florida's agricultural based prescribed fire program is equally as large (sugar cane).

owned lands including, but not limited to, the date and time of ignition, location (township, range, and cadastral section), size (acres), associated weather conditions (wind speed and direction and humidity), rate of spread, flame length, and cause (arson, campfires, cigarettes, children, debris burning, equipment, lightning, miscellaneous, railroad, and unknown) from 1981-2001. Both the wildfire data and the prescribed burning data (below) are geo-located to a Public Land Survey section (township, range, section), which is approximately a one-square mile rectangle. This is our unit of observation.

From 1981-2002 there were 31,603 wildfires in the SJRWMD, with almost half of them (48%) coming from non-incendiary human-caused sources (accidental ignitions), followed by arson (29%), and lightning (23%). The SJRWMD (and Florida in general) fire season appears to begin late-winter/early-spring and last until the middle of the summer, with burned area peaking around May and June.

Wildfire Management

The FDOF provided a second dataset that details all prescribed fire activities within the state (in order to conduct a prescribed burn in Florida, a permit must be obtained from the FDOF). Permit data includes information on the location (located by the township, range, and cadastral section), reason/type (hazard reduction, prior to seeding, site preparation, disease control, wildlife, ecological, or other), and total size (in acres). The dataset includes permits issued between 1989 and 2001, although full state-wide reporting did not occur until 1993.

In addition, wildfire start time and fire crew arrival time, given in the FDOF database, allows for the creation of a measure of initial attack/suppression (fire crew response time).

Climate/Weather

The El Niño Southern Oscillation (ENSO) measure used in this analysis is the Niño3 anomaly, which was obtained from the National Oceanic and Atmospheric Administration (National Oceanic and Atmospheric Administration 2002). The Niño 3 anomaly is measured as the positive (El Niño) or negative (La Niña) deviation, in centigrade, of the Pacific sea surface temperature (at a specific location). KBDI was calculated for two weather stations in the

SJRWMD region using daily data collected by the National Climate Data Center and provided by EarthInfo.

Landscape Characteristics

Section-level road and census data (population, income, and education) were created from US Census Bureau TIGER/Line GIS data. The National Land Cover Data, based on the Multi-Resolution Land Characteristics (MRLC) Consortium's land cover map (30-meter resolution grid) was used to determine landcover composition within and surrounding each section. Five landcover classes were assembled—grass (grassland/herbaceous), upland forest (deciduous, evergreen, and mixed forest), urban (low intensity residential, high intensity residential, and commercial/industrial/transportation), water (open water), and wetland (woody wetland).

Empirical Models

We specify three models—ordinary least squares, instrumental variables, and a propensity score model.

OLS

The OLS model is specified as:

$$\ln(\mathbf{w}) = f_w\left(\mathbf{X}_{\text{Treatment}}, \mathbf{X}_{\text{Cause}}, \mathbf{X}_{\text{Weather}}, \mathbf{X}_{\text{Climate}}, \mathbf{X}_{\text{Landscape}}, \mathbf{X}_{\text{FireHistory}}, \boldsymbol{\varepsilon}_{OLS}\right)$$

where **w** is wildfire (two models are estimated—wildfire size and intensity) and $\boldsymbol{\varepsilon}_{\mathbf{w}}$ is the error term; the treatment variables include fire crew response time, fire crew response time squared, and hazard-minimizing (as identified) prescribed fire over the past three years; the cause variables include wildfire ignition type (a separate dummy variable for arson and lightning, all others are included in the constant); the weather variables include wind speed, humidity, Keetch-Byram Drought Index (KBDI); the climate variables include measures of the (ENSO); the landscape and forest condition variables include location of the wildfire (latitude and longitude), elevation, slope, fuel type (a separate dummy variable for grass, pine, palmetto-gallberry, hardwood, all other types are included in the constant), amount of upland forest in the area, vegetation buildup, and forest density; the fire history variables includes the number of previous fire ignitions over the past 12 years in the area of the wildfire and in neighboring areas.

IV

The prescribed fire instrument is specified as:

$$\mathbf{p} = f_{p,Censored}\left(\mathbf{X}_{\text{FireHistory}}, \mathbf{Z}_{\text{Weather}}, \mathbf{Z}_{\text{Landscape}}, \mathbf{Z}_{\text{OPF}}, \mathbf{Z}_{\text{Community}}, \boldsymbol{\varepsilon}_{p,IV}\right)$$

where **p** is hazard minimizing prescribed fire, $\boldsymbol{\varepsilon}_p$ is the error term, any **X**'s as before, and $\mathbf{Z}_{\text{Weather}}$ includes percent of days over the past three years that relative humidity was between 30% and 50%, percent of days over the past three years that wind speed was between 6mph to 20 mph, average maximum temperature over the past three years, and average precipitation over the past three years; $\mathbf{Z}_{\text{Landscape}}$ includes longitude, latitude, elevation, slope, forest density, percent of upland forest, and water table depth; $\mathbf{Z}_{\text{Community}}$ includes the variables population, amount of residential area, distance to nearest fire department, distance to nearest school, distance to nearest hospital, and percent of population in a nursing home. The school, hospital, and nursing home variables are included to account for sensitive populations to wildfire and wildfire smoke; $\mathbf{Z}_{\text{OPF}}$ includes neighboring hazard minimizing prescribed fire over the last 3 years and other types of prescribed fire including neighboring areas. In particular, the relative humidity and wind histories, along with water table depth are included as they account for conditions when prescribed fire application is recommended (FDOF Prescribed Fire Manual). Of the 7490 observations, only 940 experienced previous prescribed burning, thus we model prescribed fire with a censored regression, as detailed in previous sections.

The fire crew response time instrument is specified as:

$$\mathbf{r} = f_r\left(\mathbf{X}_{\text{Cause}}, \mathbf{X}_{\text{Weather}}, \mathbf{X}_{\text{Climate}}, \mathbf{X}_{\text{Landscape}}, \mathbf{X}_{\text{FireHistory}}, \hat{\mathbf{Z}}_{\text{PF}}, \mathbf{Z}_{\text{Community}}, \boldsymbol{\varepsilon}_{r,IV}\right)$$

where **r** is firecrew response time and $\boldsymbol{\varepsilon}_r$ is the error term, any **X**'s as before, and $\hat{\mathbf{Z}}_{\text{PF}}$ is the predicted value (instrument) of prescribed fire. Fire crew response time is modeled using OLS.

The second stage wildfire model is estimated as:

$$\ln(\mathbf{w}) = f_w\left(\hat{\mathbf{X}}_{\text{Treatment}}, \mathbf{X}_{\text{Cause}}, \mathbf{X}_{\text{Weather}}, \mathbf{X}_{\text{Climate}}, \mathbf{X}_{\text{Landscape}}, \mathbf{X}_{\text{FireHistory}}, \boldsymbol{\varepsilon}_{IV}\right)$$

where $\hat{\mathbf{X}}_{\text{Treatment}}$ consists of the instrumented response time and prescribed fire variables and is estimated using OLS.

PSM

The propensity score for fire crew response time is estimated as:

$$\mathbf{r} = f_{r,PSM}\left(\mathbf{X}_{\text{Cause}}, \mathbf{X}_{\text{Weather}}, \mathbf{X}_{\text{Climate}}, \mathbf{X}_{\text{Landscape}}, \mathbf{X}_{\text{FireHistory}}, \mathbf{Z}_{\text{Community}}, \boldsymbol{\varepsilon}_{r,PSM}\right)$$

where response time is estimated as a backward stepwise regression (we only need to balance the covariates that affect response time and wildfire; see Rubin and Rosenbaum 1984), keeping variables that are significant at the 10% level.

The balancing condition is tested by regressing the natural log of each continuous variable on the propensity score and treatment. Dummy variables are tested using a logit specification. If the parameter on the treatment variable is not statistically different from zero, the covariate is deemed balanced (see Imai and van Dyk). All remaining variables (after selection) were found to be balanced.

The propensity score for prescribed fire is estimated as:

$$\mathbf{p} = f_{p,OLS}\left(\mathbf{X}_{\text{FireHistory}}, \mathbf{Z}_{\text{Weather}}, \mathbf{Z}_{\text{Landscape}}, \mathbf{Z}_{\text{OPF}}, \mathbf{Z}_{\text{Community}}, \boldsymbol{\varepsilon}_{p,PSM}\right)$$

where all variables have been defined before. The propensity score model is estimated OLS, again with backwards stepwise selection. While the censored model could have been applied here, the goal of the propensity score estimator is not to consistently estimate the parameter estimates, as we are not interested in the marginal effects of the covariates, rather we are just interested in an estimator that will create a balancing score. In order to achieve covariate balance, the neighboring hazard minimizing prescribed fire variable was interacted with all other covariates, including itself, and neighboring previous fire ignitions was squared.

The PSM wildfire model is estimated as:

$$\ln(\mathbf{w}) = f_{w,PSM}\left(\hat{\mathbf{X}}_{\text{Treatment}}, \mathbf{X}_{\text{Cause}}, \mathbf{X}_{\text{Weather}}, \mathbf{X}_{\text{Climate}}, \mathbf{X}_{\text{Landscape}}, \mathbf{X}_{\text{FireHistory}}, \mathbf{u}_{\text{PSM Strata}}, \boldsymbol{\varepsilon}_{PSM}\right)$$

Wildfire is model as a random effects model, where $\mathbf{u}_{\text{PSM\_Strata}}$ indexes strata defined by the propensity score. Since we have two treatments we have two scores, so placement into strata depends on the rank of the two scores (low-low, low-mid, low-high, mid-low, mid-mid, mid-high, high-low, high-mid, high-high).

Results

Results of the OLS, IV, and PSM wildfire models are presented in tables 1-3. Also included is table 4 which presents the estimated elasticities of the treatment variables[8]. The models estimating the instruments and propensity scores are not shown. All instrument and score models are significant and explain a limited amount of the variation of the dependent variable (1-5%).

All models find evidence of positive correlation (at the 5% level) between response time and wildfire size and negative correlation between time and flame length (the exception being the IV flame length model). The negative correlation is not expected. The estimated elasticities are similar for the OLS and PSM models, 0.0124 and 0.0118 for fire size, respectively, and -0.0059 and -0.0060 for fire length, respectively. The IV model find much larger elasticities, of -0.0412 for fire size and -1.0933 for flame length.

[8] The final OLS, IV, and PSM models were estimated as semilog, so the treatment effect elasticities on wildfire were calculated at their means as: $\text{elasticity} = \hat{\beta}_t \sum_{i=1}^{n} t_i$, where *t* is the treatment variable (either prescribed fire or response time). Note that while IV uses $\hat{t}$ to estimate $\hat{\beta}_t$, we use the actual value of treatment, *t*, to calculate the elasticities.

The OLS and PSM find a negative correlation between prescribed fire and fire size and length (10% level). The sign of the correlation is as expected. The elasticities for fire size are -0.0244, -0.3030, and -0.0464 for the OLS, IV, and PSM, respectively. The elasticities for flame length are -0.0204, 0.7875, and -0.0197.

Treatment Effect of Prescribed Fire[9]

We calculate the mean treatment effect from prescribed fire on wildfire acres to be -2.45 acres by OLS, -30.52 acres by IV, and -4.67 acres by PSM per wildfire and the treatment effect on flame length to be -.03 meters by OLS, -0.38 meters by IV, and -0.02 meters by PSM[10]. For the wildfire period 1996-2001, prescribed fire (from 1993-2001) reduced total wildfire acres by 2,306.03 acres by OLS, 28,684.20 acres by IV, and 4,394.80 acres by PSM, and reduced total flame lengths by 23.77 meters by OLS, 352.50 meters by IV, and 22.90 meters by PSM. The IV estimates are quite a bit higher than the OLS and PSM[11]. In a simulation (analysis not shown), IV was shown to return severely biased treatment effects when covariates in the wildfire equation that do not influence treatment were omitted (or unobserved), even when uncorrelated with the treatment variable (for instance, if *y* was omitted from equation 2.1).

VI. DISCUSSION

The question we are seeking to answer is whether or not wildfire management is paying off. Statistical difficulties in modeling wildfire behavior at policy relevant scales make quick answers challenging. After accounting for potential endogeneity of prescribed fire and fire crew response time, the we find evidence that quicker response times limits wildfire size and intensity (although the IV and PSM models were not perfectly consistent with one another) and that prescribed fire

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[9] While we can estimate the marginal treatment effect for fire crew response time, it is less straightforward to estimate the total treatment effect per fire for response time. In the prescribed fire case, we simply use the model to estimate expected wildfire when prescribed fire is set to zero, meaning no prescribed fire was applied and difference the result with what was observed. With response time, no treatment would correspond to a response time of infinity—no response, the fire just burned itself out.

[10] The treatment effect, per wildfire, is calculated as: $TE_i = \hat{\beta}_t * (\text{wildfire}_i) * (\text{treatment}_i)$, as all models are estimated as a semilog function.

[11] Again, note that when we calculate the treatment effect for the IV model, we use the actual level of treatment in the calculation rather than the instrumented level.

does provide beneficial effects against wildfire extent and intensity up to threes years (the effects were statistically weak in the IV case).

It is difficult to determine whether IV or PSM is the right model to use. Perhaps the decision should come from what we believe is more likely true—selection on unobservables or misspecification of the wildfire equation. Poor explanatory power of the instrument equations and propensity score equations is more damning in the IV case than with PSM. PSM does not require all variables that explain treatment be in the propensity score model. As previously stated, using weak instruments in IV has been shown to be out performed by OLS estimation (Bound, Jaeger, and Baker). The correlation between prescribed fire and its instrument is 0.18 and the correlation between response time and its instrument is 0.13. Our selection variables include factors related to values at risk, historic fire risk, forest and fuel conditions, climate, and historic weather. Of course it is impossible to say that we have included all possible factors influencing treatment and wildfire. We found (in our simulation not shown) the bias from misspecification of the wildfire equation to be much larger with IV than the bias from selection on unobservables in PSM.

Future research will focus on refining the IV and PSM models and to explore other methods (perhaps less parametric) for conditioning on the propensity score. In addition it may be useful to distinguish in the modeling between the smaller, frequent wildfires and larger, less common catastrophic fires, as some research shows there to be behavioral differences (Butry, Gumpertz, and Genton). Finally, future work should better explore the modeling assumptions, and how they are relevant in the wildfire case, that are made by the IV and PSM models. IV performs better than OLS and PSM when selection is on unobservables and good instruments exist. PSM outperforms IV and OLS when selection in on observables, but other forms of misspecification are present.

Parting Thoughts…

Over 129,217 acres of hazard mitigating prescribed fire was applied from 1993-2001 in the SJRWMD, and based on the PSM model, approximately 4394 acres and 23 meters of wildfire were reduced. IV, on the other hand, estimates over 28,000 acres and 352 meters of wildfire were reduced because of prescribed fire applications. It is quite a difference. Prescribed fire costs $25 an acre (on average), so SJRWMD spent roughly $3,230,425 on prescribed fire and perhaps worst case received 4394 acres less of wildfire. Meaning if the average damage averted, per acre, from wildfire was worth more than $735 per acre, then prescribed fire applications were economically justifiable. The IV results imply that the prescribed fire program is beneficial if the average damage averted, per acre, from wildfire is more than $113 per acre. Butry et al. found that on average the catastrophic wildfires in 1998 in Florida cost $1200 an acre. If wildfire acres is the only requirement of wildfire management, it appears prescribed fire is well worth it.

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TABLES

VARIABLE	LN(ACRES)	LN(LENGTH)	VARIABLE	LN(ACRES)	LN(LENGTH)
Intercept	4.3485	0.4463	**Landscape**		
	(1.0689)	(0.4645)	Latitude	-0.0043	-0.0012
Treatment				(0.0005)	(0.0002)
Response Time	0.0036	-0.0015	Longitude	-0.0028	-0.0001
	(0.0015)	(0.0007)		(0.0012)	(0.0005)
(Response Time)^2	0.0000	0.0000	Elevation	0.0063	-0.0009
	(0.0000)	(0.0000)		(0.0030)	(0.0013)
Prescribed Fire	-0.0002	-0.0001	Slope	-0.3165	-0.0451
	(0.0002)	(0.0001)		(0.1399)	(0.0608)
Cause			Fuel Type		
Arson	0.3759	0.0074	*Grass*	0.3467	-0.1165
	(0.0606)	(0.0263)		(0.0855)	(0.0372)
Lightning	0.3885	-0.0241	*Pine*	0.8159	0.2177
	(0.0649)	(0.0282)		(0.0948)	(0.0412)
Weather			*Hardwood*	-0.2225	-0.2480
Wind Speed	0.0034	0.0063		(0.1267)	(0.0550)
	(0.0060)	(0.0026)	*Palmetto-Gallberry*	0.5349	0.2222
Humidity	-0.0067	-0.0037		(0.0770)	(0.0335)
	(0.0019)	(0.0008)	Upland Forest	0.3883	0.0753
Spread Index	0.0117	0.002634		(0.1188)	(0.0516)
	(0.0028)	(0.0012)	Forest Density	0.0012	0.0013
KBDI	-0.0002	0.0002		(0.0014)	(0.0006)
	(0.0002)	(0.0001)	Vegetation Buildup	-0.0011	-0.0004
Climate				(0.0060)	(0.0004)
Nino	0.0497	-0.0179	**Fire History**		
	(0.0371)	(0.0161)	Previous Ignitions	-0.0302	0.0001
Nina	-0.1844	-0.0401		(0.0044)	(0.0019)
	(0.0908)	(0.0395)	Previous Neighboring	-0.0067	0.0057
			Ignitions	(0.0059)	(0.0026)
Prob > F	0.0000	0.0000			
R-Squared	0.0549	0.0574			

Table 1. OLS wildfire model.

VARIABLE	LN(ACRES)	LN(LENGTH)	VARIABLE	LN(ACRES)	LN(LENGTH)
Intercept	-0.2136	-0.1802	**Landscape**		
	(0.0682)	(0.3017)	Latitude	-0.0024	-0.0009
Treatment				(0.0009)	(0.0042)
Response Time	0.1703	0.0288	Longitude	-0.0005	0.0002
(predicted)	(0.0742)	(0.3283)		(0.0035)	(0.0153)
(Response Time)^2	0.0000	-0.0006	Elevation	0.0191	0.0008
(predicted)	(0.0026)	(0.0115)		(0.0064)	(0.0283)
Prescribed Fire	-0.0022	-0.0003	Slope	-0.3495	-0.0482
(predicted)	(0.0017)	(0.0076)		(0.3745)	(1.6568)
Cause			Fuel Type		
Arson	0.6658	0.0533	*Grass*	1.8763	0.0864
	(0.1618)	(0.7159)		(0.1765)	(0.7807)
Lightning	-0.1808	-0.1063	*Pine*	1.8693	0.3463
	(0.1883)	(0.8331)		(0.2744)	(1.2137)
Weather			*Hardwood*	0.8867	-0.1102
Wind Speed	0.0215	0.0090		(0.3244)	(1.4352)
	(0.0140)	(0.0620)	*Palmetto-Gallberry*	1.9321	0.3999
Humidity	0.0038	-0.0022		(0.1676)	(0.7415)
	(0.0051)	(0.0225)	Upland Forest	0.0239	0.0179
Spread Index	0.0075	0.0020428		(0.3038)	(1.3440)
	(0.0081)	(0.0359)	Forest Density	-0.0033	0.0006
KBDI	0.0003	0.0003		(0.0032)	(0.0140)
	(0.0040)	(0.0018)	Vegetation Buildup	-0.0025	-0.0006
Climate				(0.0023)	(0.0101)
Nino	-0.0118	-0.0248	**Fire History**		
	(0.0962)	(0.4256)	Previous Ignitions	-0.0695	-0.0048
Nina	0.8630	0.0992		(0.0125)	(0.0551)
	(0.2616)	(1.1574)	Previous Neighboring	0.0033	0.0074
			Ignitions	(0.0169)	(0.0749)
Prob > F	0.0000	0.0000			
R-Squared	0.0603	0.0569			

Table 2. IV wildfire model (asymptotic standard errors shown).

VARIABLE	LN(ACRES)	LN(LENGTH)	VARIABLE	LN(ACRES)	LN(LENGTH)
Intercept	-0.6088	-2.5978	**Climate**		
	(1.2685)	(0.5610)	Nina	-0.1654	-0.0483
Treatment				(0.0816)	(0.0361)
Response Time	0.0036	-0.0015	**Landscape**		
(predicted)	(0.0015)	(0.0007)	Elevation	0.0069	-0.0018
(Response Time)^2	0.0000	0.0000		(0.0022)	(0.0010)
(predicted)	(0.0000)	(0.0000)	Slope	-0.0597	-0.0552
Prescribed Fire	-0.0003	-0.0001		(0.1434)	(0.0634)
(predicted)	(0.0002)	(0.0001)	Fuel Type		
Prescribed Fire			*Grass*	0.3864	-0.1096
Neighboring Hazard PF	-0.0475	-0.0240		(0.0846)	(0.0374)
	(0.0191)	(0.0084)	*Pine*	0.8666	0.2231
Other Types PF	0.1121	0.0548		(0.0931)	(0.0412)
	(0.0464)	(0.0205)	*Hardwood*	-0.0563	-0.2371
Neighboring Other PF	0.0724	0.0296		(0.1262)	(0.0558)
	(0.0203)	(0.0090)	*Palmetto-Gallberry*	0.5982	0.2403
Community				(0.0741)	(0.0328)
Population	0.0000	0.0000	Upland Forest	-0.6720	-0.0597
	(0.0000)	(0.0000)		(0.1130)	(0.0500)
School	-0.0460	0.0043	Residential	(1.7580)	(0.1498)
	(0.0047)	(0.0021)		(0.1379)	(0.0610)
Cause			Water Table Depth	0.0128	-0.0047
Lightning	-0.0473	-0.0576		(0.0225)	(0.0100)
	(0.0571)	(0.0253)	**Fire History**		
Weather			Previous Ignitions	-0.0131	0.0014
Temperature	0.0042	0.0079		(0.0044)	(0.0020)
	(0.0039)	(0.0017)	Previous Neighboring	-0.0026	0.0053
Humidity	-0.0090	-0.0048	Ignitions	(0.0059)	(0.0026)
	(0.0017)	(0.0008)			
Prob > chi-squared	0.0000	0.0000			
R-Squared	0.0699	0.0541			

Table 3. PSM wildfire model.

	OLS		IV		PSM	
	Acres	Length	Acres	Length	Acres	Length
Prescribed Burning	-0.0244	-0.0204	-0.3030	0.7875	-0.0464	-0.0197
	(0.0018)	(0.0015)	(0.0222)	(0.0667)	(0.0034)	(0.0014)
Response Time	0.0124	-0.0059	-0.0412	-1.0933	0.0118	-0.0060
	(0.0012)	(0.0003)	(0.0030)	(0.6114)	(0.0014)	(0.0003)

Table 4. Treatment effect elasticities and standard errors.