Estimating the Effect Wildfire Management has on Fire Behavior: A Propensity-Score Matching Approach

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Wildfire Economics

Understanding tradeoffs

Economic theory

Min cost plus loss (or NVC)

Seek to minimize the cost of fire management (suppression, fuel treatments, etc.) *plus* wildfire damages (losses)

Max damages averted given input costs

Seek to maximize the damages averted from wildfire (value of areas protected from wildfire management) given costs of wildfire management

Program Evaluation

- A literature developed to explore the ability of non-experimental methods to reliably quantify the effectiveness of social programs
- It has been applied to several fields in economics and statistics, including labor, medicine, and education…and now wildfire management
- In our wildfire case, we are interested in measuring the effectiveness wildfire management has on wildfire behavior (size and intensity)
- Propensity score matching (PSM), a program evaluation technique, has several statistical advantages over traditional (parametric) regression approaches, especially in its ability to deal with endogeneity

Program Evaluation

We are interested in estimating the causal effect a group's participation in a program (termed the *treatment*) has on some variable of interest (termed the *outcome*).

Examples,

In labor studies, researchers are interested in how a training program (*the treatment*) enhances participants' wages (*the outcome*).

In epidemiological studies, researchers are interested in how a drug therapy (*the treatment*) benefits some measure the participants' health (*the outcome*).

In our wildfire study, we are interested in measuring the effectiveness of wildfire management (*the treatment*), for instance the effect of prescribed fire, on wildfire behavior (*the outcome*)

Experimentally Controlled Studies

In experimentally controlled studies, a comparison is made between the outcomes of treated observations with those untreated.

Since treatment is selected randomly, by design of the experimental method, all observations in the study have the same probability of selection into treatment. Hence, the treated group is no different than the control group, except for treatment status.

If the treated and control groups are similar in all other ways, except for treatment status, then any mean difference in group outcomes are due to the treatment.

Non-experimentally Controlled Studies

Experimentally controlled studies are often infeasible or expensive.

In an observational study, comparing the outcome from a treated group with a non-treated group (acting as the control group) may lead to biased conclusions.

When treatment selection is not experimentally controlled, implying that the probability of treatment selection is not equal between groups, then differences in the group outcomes may be a function of treatment *AND* other factors.

In the wildfire case, wildfire may not be independent of treatment selection. This occurs because the management decision to mitigate wildfire is simultaneously determined with wildfire size or risk

Fire Suppression:
While suppression effort should reduce wildfire size, either initial size or unexpected changes in fire behavior may influence the amount of suppression effort allocated.

Pre-Suppression Activities (Fuel Treatment):
While fuel treatment programs should reduce the risk of large wildfires, areas with high wildfire risk will be chosen, all else equal, for fuel treatment before areas with lower risk.

Ordinary Least Squares

In the OLS framework, we can estimate the treatment effect by regressing *y* on *t*,

$$\tilde{\mathbf{y}}_\mathbf{i} = \mathbf{x}_\mathbf{i}\beta + \mathbf{t}_\mathbf{i}\alpha + \varepsilon_\mathbf{i}$$

where

y is the outcome believed to be influenced by participation in a program

t_i denotes treatment status (1 = treatment, 0 otherwise)

x_i includes all other variables that affects outcome

α, β are estimated parameters, and α equals the treatment effect

ε_i is the error term

If $E(\varepsilon_i \mid t_i) \neq 0$, the outcome does not follow a linear-in-parameters functional form, or if the distributions of x, between the two treatment groups, are not similar, then and α and β are biased and inconsistent.

Program Evaluation Intuition

$(\text{Wildfire behavior given treatment})_i$

$-$

$(\text{Wildfire behavior given no treatment})_i$

$= (\text{Treatment Effect})_i$

Missing Information

Observed Information

For any particular wildfire *i*, we observe *either* :

That the wildfire had been treated

OR

That the wildfire had not been treated

Missing Information

However, we never observe the wildfire behavior ***that would have occurred*** if the treated wildfire *i* ***had not been treated***.

Constructing a Counterfactual

We could substitute wildfires that did not have treatment as an approximation for the wildfire behavior that would have occurred if treatment had not been applied to wildfire that had treatment

However, without any further modifications, wildfires without treatment will only proxy the counterfactual if expected wildfire behavior, pre-treatment decision, is independent of the treatment decision.

This holds in experimentally controlled studies, by design, since treatment is assigned randomly.

PSM Propositions

1. **If** we observed a set of covariates, *z*, that explain the treatment decision (process), so that accounting for these covariates, we would expect the treatment group and the non-treatment group to have the same outcome if neither were subjected to treatment (or the same outcome prior to treatment decision), and

2. **If** we can model the probability of treatment as a function of the covariates, z, termed the *propensity score*, then

3. Matching treated observations with untreated observations, based on their propensity score, creates a control group for the treated group. We can directly compare the control group with the treated group to estimated an unbiased treatment effect.

Propensity Score Matching (PSM)

- PSM matches treated and non-treated observations based on their propensity score
  - The propensity score (probability of being treated) is a function of covariates (*z*) which influence the selection decision
  - Matched pairs have the same PS, thus the probability of treatment selection is the same between treated and untreated observations (as in experimental studies)
  - Any difference in the outcome, between matched pairs, are due to the treatment.
- Nonparametric matching technique
- Eliminates “curse of dimensionality” (matches on a scalar, the PS, rather than the set of covariates, *z*.

PSM Assumptions

z is known and observable

If **y** is independent of **t**, conditioned on **z**, and if the set of covariates that comprise **z** are known and observed, PSM will yield an unbiased estimate of the treatment effect.

If the independence of **y** and **t** is conditioned on **z** and **u**, where **u** is unobserved and not included in the PSM model, then PSM will be biased.

PSM—*Empirical Analysis*

Examine the average treatment effect hazard mitigating prescribed fire has on wildfire size and intensity

We analyze 7395 wildfires in SJRWMD region in Florida from 1996-2001

- Treatment is defined as having any prescribed fire within the previous 3 years
- 938 wildfires treated, 6457 untreated

Treatment Effect—Ignoring Potential Bias

	Treated		Untreated	
	Acres	Intensity	Acres	Intensity
Sample Mean	56	932	70	923
OLS*	0.8	n/a	1.1	n/a

*OLS estimate evaluated at the mean & for small wildfires only (≤1,000 acres). Treatment is for 40 acres of prescribed burning, occurring earlier in the year, but prior to the wildfire ignition.

OLS model:
LN(wildfire size) = f(fire characteristics, climate & weather, management, landscape attributes)

Average Treatment Effect Algorithm

1. Estimate the propensity score
2. Pair observations based on the score and some matching criteria
3. Average the pair outcome difference to estimate the average treatment effect

Propensity Score Estimator

We model the probability of treatment (prescribed fire in 3-years prior to wildfire) for each wildfire as a function of:

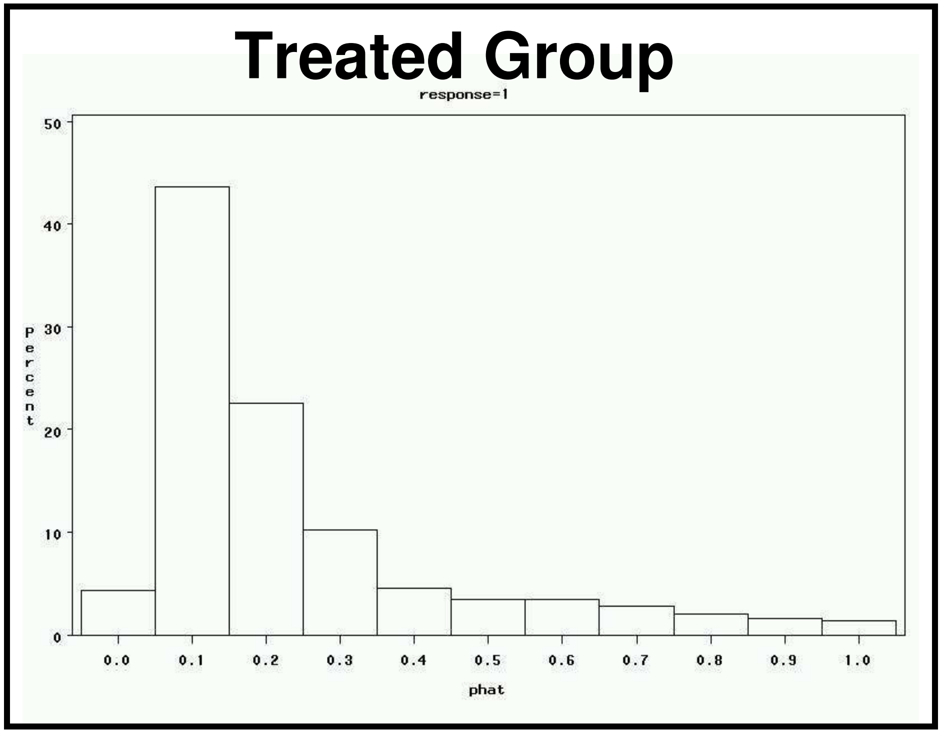
Wildfire Risk Factors

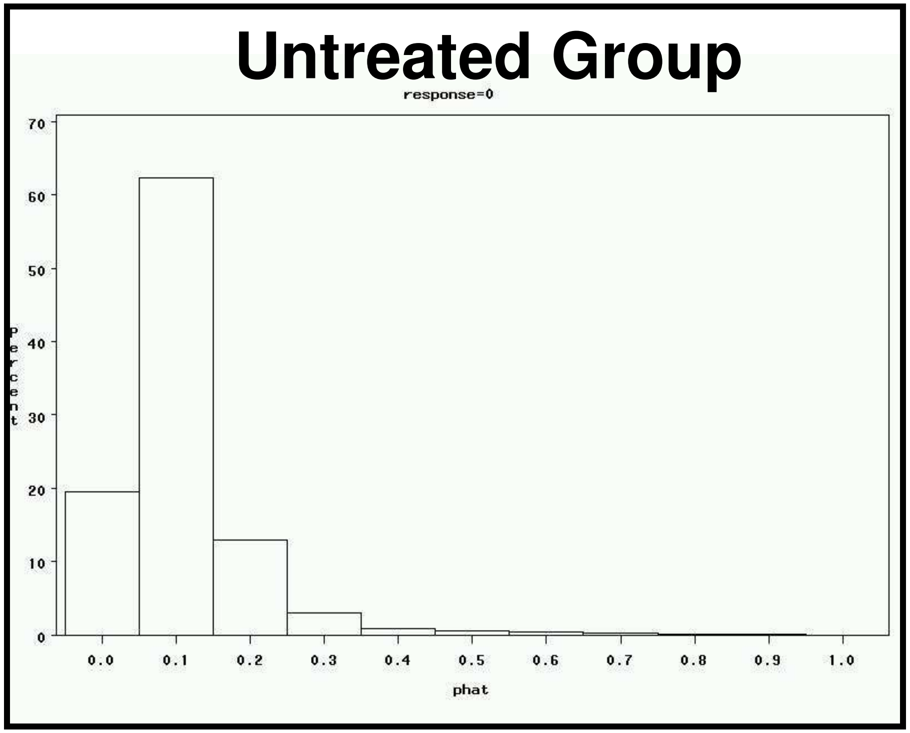
Historic ignition patterns, fuel conditions, landscape characteristics, climate and weather, previous prescribed fire, etc.

Prescribed Burning Regulations (FDOF Burning Manual)

Fuel type, weather factors, soil condition, surrounding socioeconomic characteristics (including distance to sensitive populations), etc.

Distribution of Propensity Scores



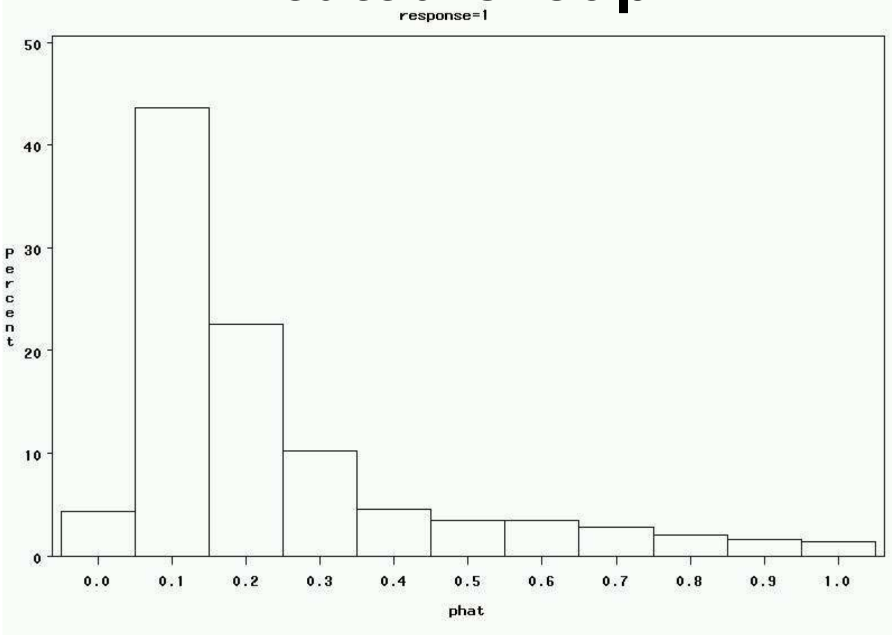


Matching Neighborhood & Weights

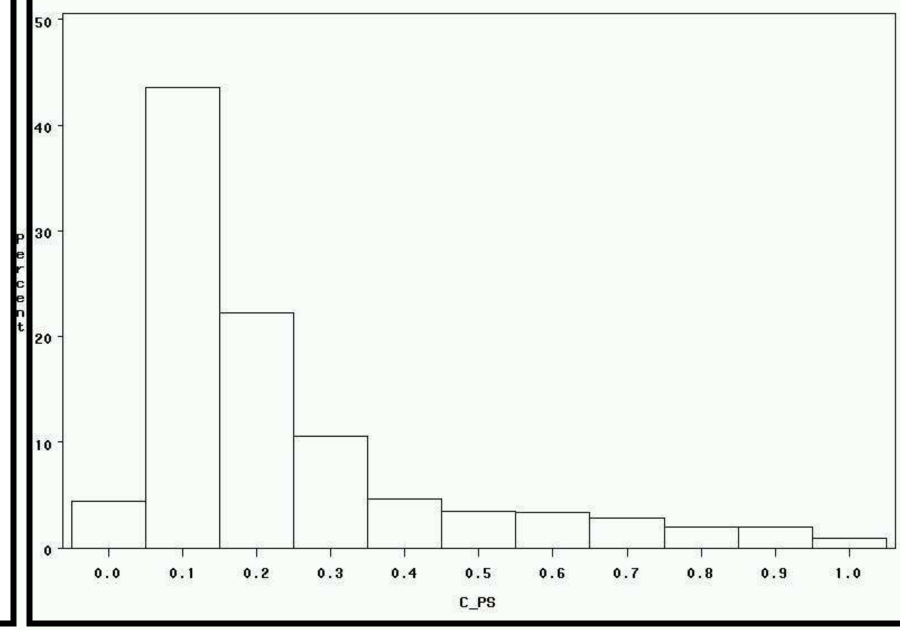
- Several matching techniques exist and differ with respect to the **matching neighborhood** and **weight**
- We use a nearest neighbor match (we match each treated with a untreated with the closest score value)
- Several other matching techniques exists

Distribution of Propensity Scores

Treated Group



Control (matched) Group



PSM Results

- Prescribed fire reduces wildfire size, on average, by 127 acres per fire.
- Prescribed fire reduces wildfire intensity, on average, by 169 kWacre/meter per fire.
  - A reduction in fireline intensity of 169 translate into a reduction in flame length of 0.82 meters per fire

Impact

- On average, treated wildfire experienced 1.9 hazard mitigating prescribed fires in the prior 3-year, averaging 137 acres treated.
  - Prescribed fires cost approximately $US 25 an acre.
  - Catastrophic wildfires cost approximately $US 1200 an acre
- On average the cost saving from prescribed fire is $US 148,975 per fire.
  - Only when the cost of prescribed fire exceeds $US 1,112 an acre, does prescribed fire fail to be cost effective

Conclusion

- We find that prescribed fire reduces wildfire size and intensity
- Appears to be almost a one-for-one tradeoff between hazard-mitigating prescribed fire and wildfire (1acre of PB yields 0.92acres less wildfire, on average)
  - Burn now versus burn later
- Based on the model, prescribed fire has mitigated 119,126 acres of wildfire over 1996-2001 in the SJRWMD.