An Economic Approach to Measuring the Impacts of Higher Temperatures on Wildfire Size in the Western United States

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Abstract

The purpose of this paper is to investigate the effect that higher temperatures will have on the size of wildfires in the western United States controlling for suppression effort, precipitation, and other factors. Using data for 466 wildfires that occurred on U.S. Forest Service land between 2003 and 2007, I find that an increase in temperature of 1 °C is associated with a 12% increase in wildfire size, holding all other factors constant. Given that current climate models predict temperatures to rise by 1.6 to 6.3 °C, this estimate suggests mean wildfire size could increase by 20% to 79%. Off-setting this increase in wildfire size would require an increase in suppression expenditures of at least 16% to 63%. For the average wildfire, this would translate into an increase in suppression expenditures of between $0.5 and $2 million.

Keywords: cost containment, endogeneity, fire economics**,** forestry

Selected Paper prepared for presentation at the 2015 AAEA & WAEA Joint Annual Meeting, San Francisco, California, 26-28 July 2015

1. Introduction

Over the past thirty years, the average size of wildfires in the United States has more than doubled, from 15 hectares per fire in the 1980s to 36 hectares per fire in the 2000s (NIFC, 2014). Most of this increase was driven by a growing number of catastrophic wildfires that exceed ~20,000 hectares like the 2002 Hayman Fire in Colorado that burned 55,846 hectares and destroyed $38.7 million in private property (USFS, 2013). Policy makers interested in responding to these events need to understand what is driving this trend.

Previous studies by ecologists and other natural scientists suggest that increases in wildfire activity have been largely driven by changes in weather variables—namely higher temperatures. The first of these studies was McKenzie et al. (2004), which regressed the number of wildfire acres burned in 11 western states from 1916-2002 on mean summer temperature and precipitation for each state. This study found that years with high summer temperatures were associated with more acres burned by wildfire.

Subsequent studies applied similar analytical methods to more spatially disaggregated datasets and found analogous results (Westerling et al., 2006; Littell et al., 2009). However, none of these studies controlled for human efforts to suppress wildfire in their regression estimates. This is important because one would expect suppression to both have a significant influence on wildfire size and be correlated with temperature for a variety of reasons. For example, higher temperatures could be associated with less suppression effort if warmer weather made conditions more dangerous for fire fighters (e.g. higher risk of heat stroke). Alternatively, higher temperatures could be associated with more suppression effort if dryer fuels mean more economic resources are threatened by fire. In either case, by excluding suppression effort, these previous studies may have significantly over (or under) stated the impact of higher temperatures on wildfire activity due to omitted variable bias.

However, trying to overcome the omitted variable problem by adding a measure of suppression effort to a regression model can introduce new problems. Specifically, wildfire size and suppression effort are jointly determined, which means that an instrumental variable estimator must be used to avoid the problem of endogeneity bias. This issue was previously identified by Johnston and Klick (2011), but they did not attempt to estimate such a model themselves.

The goal of this paper is to fill this gap in the existing literature by estimating the partial effect of temperature on wildfire size while controlling for suppression effort using data from wildfires on U.S. Forest Service land. First, I develop an economic model where wildfire size is determined by the interaction of exogenous natural factors, such as mean temperature and precipitation when a fire is ignited and in previous months, and suppression effort applied by U.S. Forest Service fire managers. Specifically, I follow Donovan and Rideout (2003) and assume the objective of fire managers is to minimize the sum of costs associated with wildfire (i.e. the cost of suppression effort plus the cost of net wildfire damages). Next, I estimate the structural equations derived from this model using data collected from a pooled cross section of 466 wildfires that occurred in the western United States between 2003 and 2007 and for which there is reliable suppression expenditure data (a proxy for suppression effort). Estimates for temperature and precipitation for the area surrounding each fire are estimated using weather-station level data obtained from the National Climate Data Center from its Global Historical Climatology Network (GHCN) Monthly database.

The remainder of the paper is organized as follows. First, I discuss the scientific literature on wildfire size to identify factors that can influence wildfire size. Second, I develop an economic model of wildfire that accounts for human suppression activity. Third, I describe the methods used to estimate the economic model I develop. Fourth, I report the results of this estimation. The paper concludes with a discussion of the results and limitations of the paper.

2. How Changes in Temperature and Precipitation and Other Factors Influence Wildfire Size

The number of hectares a wildfire will burn after it has been ignited primarily depends on five factors: 1) the stock of available biomass to burn (i.e. fuel availability), 2) the combustibility of that biomass (i.e. fuel flammability), 3) the ecology of the surrounding area, 4) the typography of the surrounding area, and 5) how much effort is exerted to suppress the fire. In the following section, I will describe how each of these factors influence the size of wildfires.

The stock of fuel available for wildfires to burn consists of different types of biomass such as dead woody material (needles, fallen branches, dried herbaceous vegetation, snags, and logs), shrubs, live trees and other vegetation (Bracmort, 2013). Each of these types of fuel contributes to wildfire activity in different ways. For example, fuels that are small in diameter, such as needles and leaves, are most important for how quickly a wildfire will spread. This is because their small size means they lose moisture quickly and therefor combust more easily (Bracmort, 2013). By contrast, larger fuels, such as branches, shrubs, and logs, are more important for how intense the wildfire will become (i.e. how much energy a wildfire will release as it burns) (Bracmort, 2013).

How much fuel is accumulated over a particular period of time depends on how much fuel is grown over that period and how much is removed. Biomass growth is supported by environmental factors such as higher precipitation. Precipitation in the months immediately preceding a wildfire are most important for determining the quantity of small diameter fuels that are available to burn, while atmospheric conditions over longer periods of time are more important for larger fuels because they take longer to grow.

Biomass removal is typically accomplished by two methods: 1) naturally by wildfire or 2) artificially by fuel removal efforts by the USFS and other agencies. Prior to the 20^{th} century, biomass removal was entirely accomplished through natural wildfires. However, from 1935 to 1971, the U.S. government was committed to a policy of suppressing all wildfires (regardless of potential benefits). This policy was known as the "10AM policy" as it called for the "fast, energetic, and thorough suppression of all fires in all locations, during possibly dangerous fire weather. When immediate control is not thus attained...the [suppression] each succeeding day will be planned and executed with the aim, without reservation, of obtaining control before ten o'clock the next morning" (Donovan et al, 2008). As a result of this complete suppression policy, tons of biomass that would have historically been removed by wildfire simply accumulated over time, contributing to the growing size of wildfires. This led to growing concerns about the sustainability of USFS wildfire policy.

In 1979, the 10AM policy was abandoned for one where the amount and timing of suppression effort was guided by benefit-cost analysis. Specifically, the goal of the USFS service became to minimize the sum of costs associated with wildfire (i.e. the cost of suppression effort plus the cost of net wildfire damages). However, over time, it became clear that the consequences of following the 10AM policy for decades were not eliminated simply by abandoning the policy itself. Ecologists argued that many areas suffered from excess fuel loads created by the exclusion of wildfires in the past that made the likelihood of larger wildfires in the future even greater. These concerns led the federal government to pursue artificial fuel removal starting in the early in 2000s.

Once fuel has accumulated, its flammability is primarily determined by moisture content. Specifically, fuel with a moisture content of up to 20%-30% can be ignited by a match, spark from a chainsaw, or more commonly from lightning (Bracmort, 2013). Moisture content is primarily determined by weather conditions prior to a fire's ignition. Higher temperatures will increase the drying capacity of the air and lower precipitation levels will make less moisture available (Routlet et al, 1992; Flannigan et al, 2009). For fine fuels, weather conditions in the weeks immediately preceding a fire are most important, because they are small and their moisture content can therefore change quickly (Bracmort, 2013).

In addition to fire availability and flammability, the ecosystem surrounding a fire determines how fuel availability and flammability interact to influence wildfire size. For example, in a relatively dry ecosystem that is dominated by grass and low density shrub vegetation types, fuel coverage may be so sparse that in some years the spread of large fires is limited by fuel availability. When such an ecosystem receives above normal precipitation, fire risks may be subsequently elevated for a time, as excess moisture leads to the growth of additional vegetation that can provides more continuous fuel coverage (Westerling and Bryant, 2008). Westerling and Bryant (2008) refer to these systems as moisture-limited fire regimes.

The topography of the area surrounding the fire is also important for how large it will grow. The three typographical characteristics that are most relevant for fire size are aspect, elevation, and slope. Aspect is the direction of the slope and it affects how much solar radiation a site receives. For example, south slopes receive much higher solar radiation and are warmer, so fuels tend to dry out sooner and more thoroughly during the fire season. Elevation affects fire behavior by influencing the amount and timing of precipitation, as well as exposure to prevailing wind. Slope influences the speed of a wildfire's spread. Specifically, as heat rises in front of the fire, it more effectively preheats and dries upslope fuels, making for more rapid combustion.

In addition to the geophysical aspects discussed above, human beings also have significant influence over how large a wildfire will grow through the amount of effort they exert on suppressing the fire. In the United States, there are multiple local, state, tribal, and Federal organizations tasked with fighting wildfires, with each organization being responsible for responding first to wildfires occurring within their jurisdiction (very large fires may require coordination of resources across multiple organizations). If a fire occurs on a national forest or national grassland, it is the responsibility of the USFS to provide an initial response. These USFS lands are grouped into nine broad geographic areas known as USFS management regions (Figure 1). Each region is managed by a "regional forester." However, the person that is actually in charge of controlling a particular fire is the incident commander.

The incident commander must establish an organization and command structure for dealing with the blaze. If the incident commander behaves in accordance with the current USFS fire management policy described above, then his ultimate objective will be to minimize the sum of all monetized wildfire related costs and damages. The specific costs of wildfire suppression will depend on the tactic used to suppress the wildfire. There are two primary fire suppression tactics incident commanders can pursue to suppress a fire: direct attack and indirect attack. A direct attack is conducted at a fire's edge and involves applying treatments directly to burning fuel such as wetting, smothering, or chemically quenching the fire. An indirect attack is conducted a distance from the fire and typically involves actions like creating a gap between the fire and unburned fuel in order to break or slow the progress of wildfire. In either case, the costs of suppression can include the labor cost of paying fire crews and the material and capital costs of using and maintaining equipment like helicopters, planes, and bulldozers (Holmes and Calkin, 2012). The damages of wildfire include value of lost timber and in some cases property damages (Donovan et al, 2008). In the next section, I formalize this general discussion about wildfire size into an economic model that can be estimated.

3. An Economic Model of Wildfire Size

Based on the discussion in the previous section, we can say that changes in temperature and precipitation in the weeks prior to a fire's ignition influence its size through their effect on fuel flammability, while changes in these variables over a longer time period influence fire size through fuel availability. In addition to temperature and precipitation, fire size is also influenced by the level of effort exerted in suppressing the wildfire as well as the ecology and topography of the surrounding area. A general function determining wildfire size can be expressed as

$$Size_i = f(T_i, P_i, Fuel_i,\ Supp_i, Ecology_i, Aspect_i, Elev_i, Slope_i) \quad \textbf{(1)}$$

where $Size_i$ is the number of hectares burned by wildfire i, T is the average temperature for the area surrounding wildfire i in the month the fire occurred, P is the total precipitation for the area surrounding wildfire i in the month the fire occurred, $Fuel_i$ is the fuel stock of the area surrounding wildfire i, $Supp_i$ is the level of suppression effort applied in controlling wildfire i, $Ecology_i$ is a dummy variable indicating which ecological region the fire occurred in, $Aspect_i$ is the aspect at the point of ignition, $Elev_i$ is the elevation the point of ignition, and $Slope_i$ is the slope at the point of ignition.

Note that all of the factors included in this function are exogenous except for suppression effort. Suppression effort is necessarily jointly determined with the number of wildfire hectares burned. Therefore, if we wish to model how many hectares will be burned each period, we must also model the decision for how much suppression effort is applied each period.

As previously discussed, the USFS has determined that suppression must be applied to minimize the total cost (TC) of wildfire. Here, TC is defined as fire-suppression costs plus net fire damages, where net fire damages can include destruction of private property, destruction of harvestable timber, etc. (Husari and McKelvey, 1997; Donovan and Rideout, 2003). Under this assumption, the incident commander solves the following cost minimization problem:

$$\min TC(Supp_i) = W^S Supp_i + ND(Size_i(Supp_i), X_i^{ND}) \qquad \textbf{(2)}$$

where W^s is the price of suppression effort, $Supp_i$ is the level of suppression effort, and ND is the level of net damages from wildfire. I assume that ND is a function of $Size_i$ (which is itself a function of suppression effort) as well as numerous other exogenous factors, X_i^{ND}, that may influence the value of damages associated with a fire of a given size (e.g. the value of property in a wildfire's path).

The first and second order conditions for this cost minimization problem are:

$$\text{FOC:} \quad W^S + \frac{\partial ND}{\partial Supp_i} = 0 \qquad \textbf{(3)}$$

$$\text{SOC:} \quad \frac{\partial^2 ND}{\partial {Supp_i}^2} > 0 \qquad \textbf{(4)}$$

The first order condition implicitly defines the optimal level of suppression effort that will be applied to controlling wildfire in accordance with USFS policy goals. Intuitively, this condition says that suppression effort will be applied until the marginal cost of that effort (W^s) equals its marginal benefit in terms of avoided damages ($-\frac{\partial ND}{\partial Supp_i}$). The second order condition tells us marginal benefit must be decreasing with additional suppression effort ($-\frac{\partial^2 ND}{\partial {Supp_i}^2} < 0$). Figure 1 illustrates the cost minimizing choice of suppression effort.

<<Insert Figure 1 About Here>>

Assuming that the conditions of the Implicit Function Theorem are satisfied, we can solve the first order condition for the optimal level of suppression effort, which will be a function of exogenous variables:

$$Supp_i^*(W^s, X_i^{ND}, T_i, P_i, Fuel_i, Ecology_i, Aspect_i, Elev_i, Slope_i) \quad \mathbf{(5)}$$

Substituting this level of suppression back into Eq.1 yields the optimal wildfire size, which is the wildfire size we would observe in the data.

$$Size_i^* = (T_i, P_i, Fuel_i, \ Supp_i^*, Ecology_i, Aspect_i, Elev_i, Slope_i) \quad \mathbf{(6)}$$

4. Estimating the Economic Model

In order to estimate the theoretical model derived above, one must choose which variables to include in the estimated model, the parametric functional form that will be used, and select an estimator to estimate the parameters themselves.

In terms of which variables to include in the estimated model, this question is largely answered by the economic model itself. However, some of the variables included in the economic model could not be included in this study model due to data limitations, so I had to use suitable proxies. First, actual suppression effort cannot be observed, so I use inflation-adjusted suppression expenditures. Expenditures make a reasonable proxy for suppression effort, since I would expect that more money being spent suppressing a fire would indicate more resources being applied to fight the fire.

Second, an explicit measure of the fuel stock present at each fire is not available, so I use average precipitation anomaly for the area surrounding the fire's point of ignition. Precipitation anomaly estimates should make a reasonable proxy for fuel stock surrounding a particular fire, because (as previously discussed) higher than normal precipitation levels will support fuel growth and therefore be associated with greater fuel stocks. Calculating this variable is completed in two steps. First, precipitation anomaly for each month prior to the fire's ignition is calculated as the difference between precipitation that was actually observed in that month and the mean precipitation for that month from 1980 to 2000. Second, a simple average is taken for the estimated precipitation anomaly across each of the six months prior to the fire's ignition.

Third, the ecological characteristics of the area surrounding each fire are also difficult to determine. For the purposes of this study, I categorize fires based on whether or not they occurred in a "dry" ecosystem, which I define as a region where annual losses of water through evaporation at the earth's surface exceed annual water gains from precipitation. To capture ecological differences closer to the fire itself, I included a categorical variable for the type of vegetation observed at the fire's point of ignition.

In addition to these proxies, I also included categorical variables for the USFS management region the fire was located in and the year in which the fire occurred to capture unobserved factors that differ across geographic regions that unobserved factors that are common to all regions but vary across time.

A log-level functional form is used for this model specification because inspection of the model residuals suggested that the underlying disturbances better approximated a normal distribution. Therefore, in this analysis, I estimate the following model:

Model #1: $$\ln(Size_i) = \beta_0 + \beta_1 T_i + \beta_2 P_i + \beta_3 P\_Anom_i + \beta_4 \ln(SuppExp_i) + \beta_5 Dry_i + \beta \quad Grass_i + \beta_8 Slope_i + \beta_9 Aspect_i + \beta_{10} Elev_i + \sum_j^4 \beta_j USFS_{ji} + \sum_k^4 \beta_k Year_{ki} + u_i \qquad (7)$$

The variables are defined as follows:

- $\ln(Size_i)$ = the natural log of the number of hectares as burned by fire i,
- T = average temperature (measured in °C) of the area surrounding fire i in the in the month it was ignited,
- P = total precipitation (measured in millimeters) in the area surrounding fire i in the month it was ignited,
- $\ln(SuppExp_i)$ = natural log of federal suppression expenditures incurred fighting fire i,
- P_Anom = average monthly precipitation anomaly for area surrounding fire i for the six months prior to its ignition.
- Dry = a dummy variable equaling 1 when fire i occurred in a dry ecoregion,
- Grass = a dummy variables equaling 1 when vegetation at the fire's point of ignition was recorded as "grass,"
- Aspect = recorded aspect at the point of ignition,
- Elev = recorded elevation of the point of ignition in feet,
- Slope = recorded percentage slope at the point of ignition,
- USFS = dummy variable equaling 1 when fire i occurred in USFS region j,

- Year = is a dummy variable equaling 1 when fire i occurred in Year k,
- u = a disturbance term that is assumed to heteroskedastic.

In addition to estimating this main effects model, I also estimate a model where the variable for precipitation anomaly is interacted with the "dry" categorical variable. I estimate this model to see whether the partial effect of precipitation is different for moisture-constrained ecological regions. Specifically, I estimate the following model:

$$\textbf{Model \#2}: \ln(Size_i) = \beta_0 + \beta_1 T_i + \beta_2 P_i + \beta_4 P\_Anom_i + \beta_4 (P\_Anom \times Dry_i) + \beta_5 \ln(SuppExp_i) + \beta_6 Dry_i + \beta_7 Grass_i + \beta_8 Slope_i + \beta_9 Aspect_i + \beta_{10} Elev_i + \sum_j \beta_j USFS_{ji} + \sum_k \beta_k Year_{ki} + u_i \quad (8)$$

Based on the scientific discussion above, I would expect that changes in P_Anom would have a greater impact on the size of wildfires in "dry" ecological areas that are moisture-constrained.

Estimating these two models requires the use of an instrumental variables estimator, because including suppression effort as an independent variable likely introduces endogeneity bias. I use a two-stage least squares (TSLS) estimator with heteroskedasticity-robust standard errors. The instrumental variable that is used in this estimation is the distance from a fire's point of origin to the nearest populated area.

The Choice of Instrument

A valid instrumental variable must satisfy two conditions. First, the instrument must be correlated with the endogenous variable. Second, the instrument must be uncorrelated with the error term in the explanatory equation (in this case u_i in Eq.9). I chose distance as an instrument because I believe it satisfies both of these conditions.

The first condition is satisfied because there are strong theoretical reasons to suspect that less suppression effort will be applied to fires occurring father away from populated areas. Specifically, a fire that is farther away from a population center may result in fewer damages, since there would be fewer homes and businesses to destroy. This would lower the marginal benefit of suppression (represented in the model above as a decrease in X^{ND}) and therefore reduce the optimal level of suppression effort applied. Alternatively, a wildfire that occurs farther away from a population center may be harder for firefighters to access and thus more costly to fight. This would increase the marginal cost of suppression (represented in the model above as an increase in W^S) and therefore reduce the optimal level of suppression effort applied. In either case, the theoretical model predicts that less suppression effort will be exerted in fighting fires that are further away from population centers. This model prediction can be directly tested by looking at the first-stage results of the two-stage least squares regression.

It is more difficult to demonstrate that the second condition that a fire's distance from the nearest populated area is uncorrelated with the error term because this cannot be tested empirically. However, there are strong reasons to believe this second condition is satisfied. Specifically, this is because the scope for distance to influence wildfire through any pathway other than suppression effort is quite limited. There is no reason to suspect that fires farther away from populated areas face systematically different temperatures or precipitation than fires closer to populated areas. Similarly, there is no reason to suspect that fires farther from populated areas have systematically different typographical characteristics.

The only path through which distance could directly influence wildfire size is fuel loads. Specifically, it is possible that fuel loads closer to populated areas are systematically lower because there are more human-caused ignitions in these areas happen more frequently. This is due to the fact more people can visit forests that are closer to population centers, which increases the likelihood of fires being caused by campfire, misplaced cigarettes, arson, etc. Although no study has been conducted on whether fuel loads are systematically different in forests close to population centers, there are two reasons to doubt that more human-caused fires would significantly impact fuel loads of forests included in my analysis. First, human-caused ignitions are much rarer in the western United States, which is the focus of this study, than other parts of the country. Specifically, from 2000-2008, human-caused ignitions accounted for only 35% of total ignitions with an identifiable cause in western USFS regions, compared with 71% in eastern regions (Prestemon et al, 2013). Second, when human-caused wildfires do occur, they tend to be significantly smaller than naturally-caused wildfires, which would limit their impact on fuel availability. There are three reasons why human fires stay small: 1) they often occur outside the fire season, 2) they occur in vegetation that does not sustain large fires, and 3) they occur in areas where fires are immediately suppressed (Calef et al., 2008). For these reasons, I argue that distance to the nearest population center can be considered exogenous to the size of wildfires included in this analysis.

5. Data

The primary data source for this study is the National Interagency Fire Management Integrated Database (NIFMID), which contains data on characteristics of all wildfires controlled by the USFS including the number of acres burned by each fire, the geographic coordinates of the fire's point of origin, and various measures of the suppression effort that was expended controlling the fire. However, previous analyses have found that suppression expenditures estimates included in the NIFMID cannot always be taken at face value. For example, in FYs 2000 and 2002 the Forest Service spent more than $1 billion on suppressing wildfires. Yet, the sum of suppression expenditures included in the NIFMID only totaled $655 and $629 million, respectively (Gebert et al. 2007). This discrepancy was partly driven by the fact that many fires do not have suppression expenditure estimates recorded for them.

Therefore, for purposes of this study, I use a subset of the database that was used in Donovan et al. (2011). The Donovan et al. database only includes data for wildfires occurring between 2003 and 2007 where the USFS was the recorded protection agency or the majority of the acres burned were under USFS jurisdiction and where reasonable estimates of suppression expenditures could be obtained. Specifically, I analyze data for the 466 of these fires that occurred in USFS Regions 1, 3, 4, 5, and 6. I focus on these five regions for two reasons. First, understanding fires that occur in this region would be of greatest interest to policy makers because they account for over 75% of wildfire acres burned between 1978 and 2009. Second, by narrowing my focus to a particular region of the United States, I reduce some of the policy and ecological heterogeneity across fires. The location of each of the 466 fires is illustrated in Figure 2.

<<Insert Figure 2 about Here>>

Descriptive statistics for each of these variables used to estimate the models described above are reported in Table 1. Sources and methods for collecting this data are provided below.

<<Insert Table 1 about Here>>

Exogenous Variables

Measures of the average temperature and precipitation for the area surrounding each fire were constructed using weather-station level data obtained from the National Climate Data Center from its Global Historical Climatology Network (GHCN) Monthly database.[1] Specifically, I took an inverse-distance weighted average of monthly temperature and precipitation means for every station within 250 miles of a wildfire's point of origin. I chose to use an inverse-distance weighted average to reflect the fact that weather conditions closer to the origin of the fire is more important to wildfire size. I chose a radius of 250 miles to make sure that all weather observations that are relevant to a wildfire's size are included in my estimates. Although the exact radius of 250 miles was arbitrary, it is possible that precipitation that fell many miles from the origin of a fire could still support the growth of fuel surrounding a fire by traveling along streams, rivers, and underground.

Data on whether a fire occurred in a "dry" ecosystem or not was obtained by intersecting the coordinates of a fire's point of origin with the Ecological Provinces geographic information systems (GIS) layer developed by the USFS ECOMAP Team. A dry ecosystem is defined in this dataset as a region where estimated annual losses of water through evaporation at the earth's surface exceed annual water gains from precipitation.

Data on the topography and other characteristics of the area at each fire's point of ignition were obtained from the National Interagency Fire Management Integrated Database (NIFMID) by Donovan et al (2011). Specifically, data were collected on degree of the slope, the aspect, and the elevation at the fire's point of origin as well as whether the fire occurred in a grassy area or not.

[1] The GHCN Monthly database includes monthly averages of weather observations from over 70,000 surface stations across the world dating back to the year 1900.

Endogenous and Instrumental Variables

Data on suppression expenditures were obtained from Donovan et al. (2011). These suppression expenditure estimates were adjusted to 2002 dollars using the Consumer Price Index. Data on distance was also obtained from Donovan et al. (2011). Specifically, they calculated distance from each fire to the nearest census-designated place (this is an area of concentrated population, such as towns or cities, which the United States Census Bureau designated for statistical purposes).

6. Results

Testing Instrument Strength

The first-stage results for Model 1 and Model 2 are reported in Table 2 in columns 2 and 3 respectively. As theory would predict, suppression expenditures are negatively associated with a wildfire's distance to the nearest population center in both models. Specifically, in both models, a 10 mile increase in the distance from a fire's point of ignition to the nearest population center is associated with a 20% decrease in suppression expenditures. This relationship is statistically significant in both models.

The strength of the instruments is more formally tested by using the procedure described in Stock and Yogo (2005). Specifically, they show that for a single endogenous variable model, the bias of the IV estimator relative to that of the OLS estimator can be tested by comparing the first stage F-test statistic on the excluded instrument to critical values that they calculated. For the purposes of this paper, I use the Stock and Yogo method to test the null hypothesis that the maximum bias of the TSLS estimator relative to the OLS estimate is at least 20%. Stock and Yogo report that the 5% critical value for this test is 6.66. Because I estimate the F-statistic on the excluded instrument to be 7.44 in Model 1 and 7.34 in Model 2, I reject the null hypothesis for both models. I take this as evidence that weak instrument bias is not a major problem for my coefficient estimates.

<<Insert Table 2 about Here>>

The Partial Effect of Temperature and Precipitation on Wildfire Size

The TSLS results for the first model specification are reported in Table 3 in column 4. I find that fires were larger in areas that had higher temperatures in the month they ignited. Specifically, a 1 degree increase in temperature is associated with a 12% increase in wildfire size on average, holding everything else constant.

<<Insert Table 3 about Here>>

Also as expected, I find that fires were smaller in areas that had less precipitation in the month the fire was ignited. Specifically, a decrease in total precipitation of 1 millimeter during the month a fire occurs will increase wildfire size by 37% on average, holding everything else constant. This result is consistent with the notion that contemporaneous precipitation levels are most important for fuel flammability.

In addition to the contemporaneous effects of precipitation on wildfire size, we also see that precipitation in previous periods had a significant impact on wildfire size. Specifically, a 1 millimeter average precipitation anomaly over the previous six months increases wildfire size by 46% on average, holding everything else constant. This result is consistent with the notion that heavy precipitation in the months prior to a fire's ignition can lead to larger wildfires by creating more fine fuels.

The Influence of the Surrounding Ecosystem on Sensitivity to Changes in Weather Variables

The results of the second model specification are reported in Table 3 in column 5. As expected, dry ecosystems are much more sensitive to changes in precipitation than non-dry ecosystems. One can see this by looking at the interaction effect between precipitation anomaly and ecosystem type. Specifically, a 1 millimeter increase in the average precipitation anomaly over the previous 6 months will increase wildfire size by 95% in dry ecosystems as opposed to only 29% in non-dry ecosystems. A joint hypothesis test conducted using the Wald test statistic reveals that this result is significant at the 1% significance level.

Comparison to OLS Estimation Results

In addition to the TSLS estimates of Models 1 and 2, I also provide OLS estimates of each model in Table 3 in column 2 and 3 respectively. As we can see, these estimates are markedly different from each other. This is not what we would expect from two consistent estimators. The sign on the coefficient for suppression effort is also positive and strongly significant, which is the opposite of how we would expect suppression to influence wildfire size. Similarly, the wildfire size seems less sensitive to changes in temperature and wildfire size when looking at the OLS estimates than the TSLS estimates. A Wu-Hausman test formally confirms that we reject the null hypothesis that the OLS estimates are consistent at the 5% level. This makes sense given that we would expect wildfire size and suppression effort to be jointly determined, which would make OLS biased and inconsistent.

7. Conclusion

The results presented in this paper can be of great use to USFS policy makers that want to anticipated how higher temperatures from Climate Change will influence wildfire size. For example, according to the PCM-B2 and HadCM3 climate models, temperatures in the western United States are expected to increase between 1.6 C and 6.3 C in the period 2070 to 2100 relative to temperatures in the 1970-2000 period (McKenzie, 2004). Given that the results presented above predict that a 1 C increase in temperature will increase wildfire size by 12%, this would imply current climate projections suggest the mean wildfire size will increase by 20% to 79%. To put this into perspective, we can calculate a lower-bound for how much suppression expenditures would have to increase to off-set this increase in wildfire size. Specifically, based on the results of Model 1 in Table 3, we can construct a 95% confidence interval for the population parameter for the coefficient ln(SuppExp) that ranges from -1.24 to 0.47. Using the lower bound of this interval suggest that if the USFS wanted to increase suppression efforts to completely offset an increase in wildfire size of 20-79% they would need to increase suppression expenditures by at least 16-63%. In my dataset, mean suppression expenditures was estimated to be $3.3 million. This means suppression costs on the average wildfire could increase $0.5-$2 million.

It is important to understand the limitations of these results. Specifically, these results hold fuel and ecosystem characteristics constant, when in fact these might change over time. For example, as wildfires become larger, this could result in more fuel being removed from national forests over the long run, which could mitigate the effects of higher temperatures on wildfire size. Measuring the importance of such changes is beyond the scope of this study, but they do suggest that caution should be taken when using these results to extrapolate impacts of climate changes in the distant future.

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9. Figures and Tables

Figure 1. Illustration of Economic Model

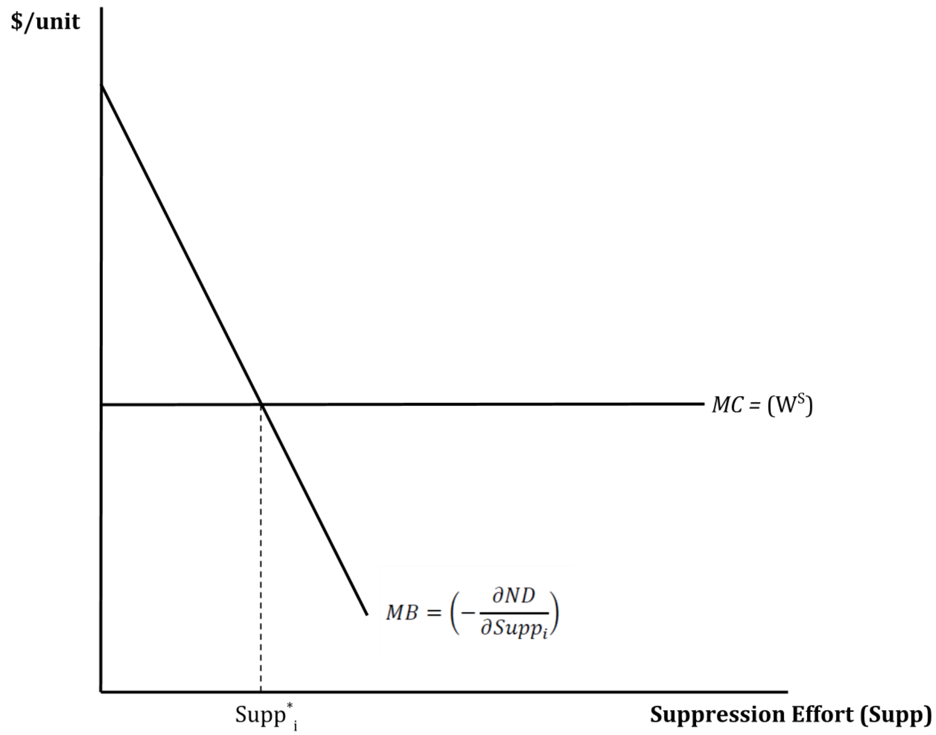

Figure 2. Location of Wildfires Included in Dataset

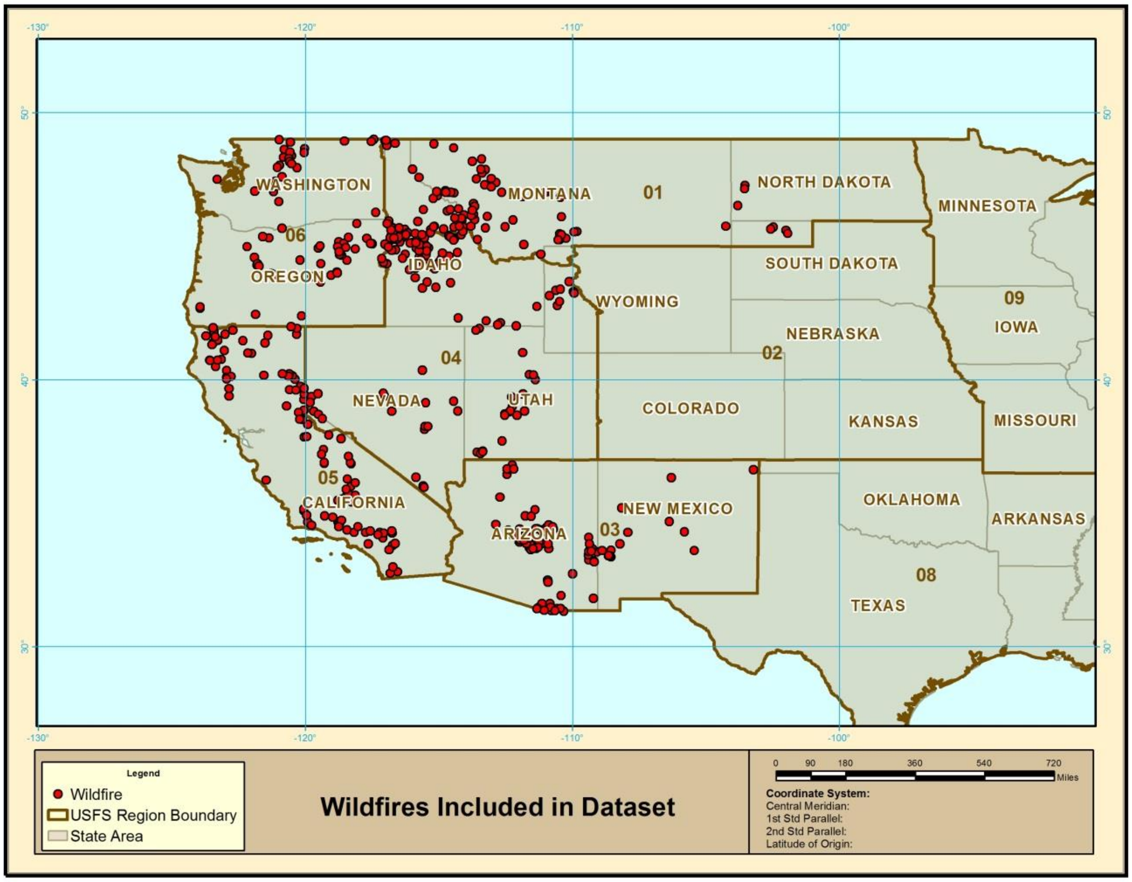

Table 1. Descriptive Statistics

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Size (acres)	466	10,118.54	27,753.53	100.00	280,059.00
T (°C)	466	19.36	4.49	1.91	29.42
P (millimeters)	466	1.57	0.87	0.02	5.19
P_Anom (millimeters)	466	0.22	0.81	-3.26	3.59
SuppExp ($2006)	466	3,366,152.00	7,129,091.00	1,305.31	98,700,000.00
Dry (1=dry region)	466	0.21	0.41	0.00	1.00
Grass (1=grass fuel)	466	0.36	0.48	0.00	1.00
Aspect (degrees)	466	4.68	2.35	0.00	9.00
Elevation (feet)	466	5,284.74	1,971.12	43.00	10,000.00
Slope (% slope)	466	38.95	23.93	0.00	150.00
USFS Region 3	466	0.20	0.40	0.00	1.00
USFS Region 4	466	0.25	0.43	0.00	1.00
USFS Region 5	466	0.20	0.40	0.00	1.00
USFS Region 6	466	0.17	0.37	0.00	1.00
2003	466	0.02	0.15	0.00	1.00
2004	466	0.15	0.35	0.00	1.00
2005	466	0.18	0.39	0.00	1.00
2006	466	0.34	0.47	0.00	1.00
Distance	466	15.96	10.61	0.39	70.14

Table 2. Results From First-Stage of TSLS Regression (n=466)

Variable	Model 1	Model 2
T	0.1***	0.09***
	(0.02)	(0.02)
P	-0.23**	-0.24**
	(0.10)	(0.1)
P_Anom	0.07	-0.02
	(0.12)	(0.13)
P_Anom×Dry		0.33
	(-)	(0.2)
Dry	-0.44	-0.45
	(0.28)	(0.28)
Grass	-1.31***	-1.34**
	(0.18)	(0.18)
Aspect	0.01	0.01
	(0.04)	(0.04)
Elevation	<0.01*	<0.01*
	(<0.01)	(0.01)
Slope	<0.01	<0.01
	(0.01)	(<0.01)
USFS Region 3	-0.41	-0.32
	(0.34)	(0.35)
USFS Region 4	0.04	0.05
	(0.29)	(0.29)
USFS Region 5	0.32	0.32
	(0.31)	(0.31)
USFS Region 6	1.23***	1.26***
	(0.28)	(0.28)
2003	0.49	0.55
	(0.64)	(0.65)
2004	0.03	0.04
	(0.26)	(0.26)
2005	-0.07	-0.08
	(0.28)	(0.28)
2006	0.03	0.07
	(0.23)	(0.23)
Distance	-0.02***	-0.02**
	(0.01)	(0.01)
Constant	12.08***	12.14***
	(0.63)	(0.63)
R^2	0.26	0.26

Note: *** denotes p-value < 0.01, **p-value < 0.05, *p-value <0.10.

Table 3. OLS and TSLS Estimations of Wildfire Size Model (n=466)

	Dependent Variable: ln(Size)			
	OLS Coefficients		TSLS Coefficients	
Variable	**Model 1**	**Model 2**	**Model 1**	**Model 2**
ln(SuppExp)	0.64*** (0.04)	0.63*** (0.04)	-0.39 (0.44)	-0.40 (0.44)
T	0.02 (0.02)	0.02 (0.02)	0.12** (0.05)	0.12** (0.05)
P	-0.14* (0.09)	-0.16* (0.09)	-0.37** (0.16)	-0.4** (0.17)
P_Anom	0.41*** (0.11)	0.34*** (0.12)	0.46*** (0.16)	0.29* (0.18)
P_Anom×Dry	(-)	0.31 (0.19)	(-)	0.66** (0.33)
Dry	0.12 (0.22)	0.1 (0.22)	-0.28 (0.41)	-0.32 (0.42)
Grass	0.06 (0.16)	0.04 (0.16)	-1.26** (0.62)	-1.32** (0.63)
Aspect	-0.04 (0.03)	-0.05 (0.03)	-0.03 (0.05)	-0.03 (0.05)
Elevation	<0.01 (0.01)	<0.01 (0.01)	<0.01 (0.01)	<0.01 (0.01)
Slope	<0.01 (0.01)	<0.01 (0.01)	<0.01 (0.01)	<0.01 (0.01)
USFS Region 3	0.45 (0.27)	0.53* (0.28)	0.05 (0.48)	0.23 (0.47)
USFS Region 4	0.26 (0.21)	0.26 (0.21)	0.23 (0.35)	0.24 (0.36)
USFS Region 5	-0.78*** (0.24)	-0.77*** (0.24)	-0.36 (0.4)	-0.35 (0.41)
USFS Region 6	-0.45* (0.23)	-0.43* (0.23)	0.83 (0.65)	0.89 (0.66)
2003	0.55 (0.47)	0.6 (0.48)	1.16 (0.94)	1.27 (0.96)
2004	-0.94*** (0.22)	-0.94*** (0.22)	-0.96*** (0.33)	-0.96*** (0.33)
2005	-0.93*** (0.23)	-0.95*** (0.23)	-1*** (0.36)	-1.04*** (0.36)
2006	-0.61*** (0.18)	-0.56*** (0.18)	-0.61** (0.3)	-0.52* (0.30)
Constant	-1 .00 (0.67)	-0.89 (0.67)	11.04** (5.22)	10.39* (5.31)

Note: *** denotes p-value < 0.01, **p-value < 0.05, *p-value <0.10.