Burning down the house: Wildfire suppression and distributional effects of responses to natural disasters

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Abstract

We examine the distributional consequences of responses to natural disasters using wildfire management. Wildfire is a growing concern in the western U.S. There, wildfire suppression expenses are largely borne by federal and state governments, which are motivated to prevent fires from damaging homes. We use home sales prices, together with data on historical wildfires to examine whether wildfire managers give greater importance to the defense of more expensive homes when deciding how to manage wildfires. Since suppression effort within a wildfire incident is difficult to observe, our empirical strategy combines historical wildfire perimeters with wildfire perimeters simulated using the US Forest Service fire simulation software FARSITE, and assumes that their difference is due to a combination of suppression effort and random error. We then relate this measure of suppression effort to home prices.

I. INTRODUCTION

Around the world, governments play a large role in managing natural resources and the environment. While this is generally supported via public goods arguments regarding the nature of environmental goods and services, environmental advocates have increasingly expressed concern about equity implications of government management. It is well-established that in choosing their places of residence, individuals tend to sort across incomes and willingness-to-pay for public goods such as environmental quality [Banzhaf & Walsh 2008; Cameron & McConahal 2006]. Such sorting results in efficient levels of locally provided public goods [Tiebout 1956], but it also may lead central governments to target the provision of public goods toward more politically-connected groups. Therefore, sorting may exacerbate environmental justice concerns over the provision of environmental quality.

Previous research has investigated top-down allocation of environmental quality in several other contexts, including zoning laws [Shertzer, Twinam, & Walsh 2014], hazardous waste clean-up [Gamper-Rabindran & Timmins 2011; Burda & Harding 2014], and air quality regulations and enforcement [Konisky 2009; Fowlie, Holland, & Mansur 2012]. However, we are not aware of any research that has examined potential inequities within another important sphere of environmental management, responses to natural disasters. Governments are often relied upon to respond to large natural disasters. However, these responses, which may encompass damage mitigation and relief programs, must sometimes be apportioned among competing interests due to resource constraints. Little research has investigated whether politicians and government agents target responses natural disasters in ways that will be politically beneficial.

In this paper, we investigate the political motivations of emergency response within the context of wildfire suppression. Due to a combination of factors, including climate change [West [erling et al. 2006] and the legacy of wildfire suppression [Allen et al. 2002; Schoennagel, Veblen, & Romme 2004], wildfire severity in the region has increased in the western U.S. In addition, as more move into residential areas adjacent to or intermingling with wildlands—

* A thank you or further information
areas known collectively as the wildland urban interface—a greater number of homeowners are exposed to wildfire risk (Theobald & Romme 2007). These factors have contributed to a recent escalation in the damages from wildfires and the cost of managing them (Haldane 2013, Hand et al. 2014). Wildfire management in the western U.S. provides an appealing setting to test political motivations underlying government emergency responses for several reasons. First, nearly half of western U.S. land is owned by the federal government, and the federal government plays a primary role in the management of wildfires in that region. Second, wildfires in the western U.S. are frequent and their initial locations are arguably exogenous conditional on a simple set of controls. Finally, despite the policy relevance of wildfire management within the western U.S., there exists little empirical research into wildfire suppression decision-making.

We are interested in testing whether wildfire managers preferentially commit greater resources toward protecting more politically valuable or connected homes. Unfortunately, it is difficult to observe how resources are allocated within an individual wildfire incident (e.g., to which portion of the fire perimeter are the majority of resources committed toward defending). Moreover, characteristics of homes such as price may be endogenous to their fire risk, for example if homeowners prefer to live near forested areas or on the tops of hills, locations that are more vulnerable to fire risk. To overcome these challenges, our strategy is to compare observed fire perimeters to fire perimeters simulated using a fire spread model that assumes no suppression. The difference between realized fire perimeters and predicted fire perimeters we assume to be due to fire suppression effort, as well as random noise; therefore, we take this difference to be a measure of the degree of fire suppression effort fire managers committed to a fire in any given direction.

We focus our attention specifically on California, in years 2000-2014. Wildfire is of special concern in California due to the frequency of wildfires and the number of homes within the wildland urban interface. Across California, 32.6% of housing units are located within the wildland urban interface (Radeloff et al. 2005). Every year, homes in California are lost to wildfire; in particularly devastating years, thousands of homes may be destroyed, as happened during the 2015 wildfires in northern California. To evaluate whether political forces influence which homes ultimately are destroyed by wildfire, we use an extensive data set of housing locations and characteristics. Additionally, we compile fire ignition locations and remotely sensed geospatial fire perimeter data for all California fires in the study period that occurred within 5 km of a WUI census block. Finally, we gathered the necessary weather and landscape data to assemble a data set of simulated fire perimeters. Our goal is to use these data to provide insight into how political motivations influence the environmental management, and responses to natural disasters in particular.

A potential concern is that the distribution of homes within the wildland urban interface does not match the overall distribution, making this a suboptimal context in which to study the distributional effects of government responses to natural disasters. If WUI homeowners are predominantly high income, variation in income within the WUI may not be sufficient to provide a clear window onto distributional motivations to government responses. In order to investigate this, figure 1 provides a kernel density plot of the distribution of mean incomes within WUI and non-WUI Census tracts in California. The distribution of mean incomes within Orange County, a wealthy California county, census tracts is provided as a frame of reference. WUI census tracts are slightly wealthier than non-WUI census tracts, and have slightly lower variation in income. However, the WUI and non-WUI distributions are fairly similar, providing support for the idea that the wildland urban interface is an

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1We consider a tract a WUI Census tract if it contains at least one Census block categorized as a WUI block by (Radeloff et al. 2008).
appropriate setting in which to examine distributional implications of disaster response.

The rest of the paper proceeds as follows. First, I develop a simple theory of wildfire suppression decision-making, which will provide insight into how managers might think about suppressing a fire that has potential to do damage in multiple directions of spread. Next, I introduce our empirical model and discuss the data. Finally, I discuss steps remaining to take this project to completion.

II. THEORY

In order to fix ideas regarding the allocation of suppression effort within a wildfire incident, this section will develop a simple model of the wildfire managers’ decision problem. To begin, imagine that a fire begins with ignition at point \( s = 0 \) and that the fire spreads in one direction, with distance in that direction given by the variable \( s \). Ignitable fuels at each point \( s \) are given by \( g_s \), and housing stock is given by \( h_s \). If a fire burns to location \( s \), the entire housing stock at that point is lost. At each point \( s \), the probability the fire burns out and burns no further is a function of both fuels in that location and \( e_s \), effort expended at location \( s \) toward suppressing the fire. Therefore, we write the probability the fire is extinguished at point \( s \) as \( f(e_s, g_s) \), and we assume \( f(\cdot) \) has the following properties:

\[ f_S < 0, f_C > 0, f_{ee} < 0, f_{eg} < 0. \quad (1) \]

This says that the probability a fire is extinguished at point \( s \) is decreasing in the fuels at that point and increasing in suppression effort. There are diminishing marginal returns to suppression effort, and the returns to suppression effort are diminishing in the amount of fuels at location \( s \).

Next, we assume that the fire has the potential to spread in multiple directions, indexed by \( l \). Additionally, we assume that the fire burns at unit speed in each direction from its ignition point. Therefore, at time \( s \), the the fire is at distance \( s \) from the fire in direction \( l \), and also at distance \( s \) from the fire in direction \( m \), conditional on it having burnt that far in each direction. This assumption allows us to effectively treat time and distance from the ignition point as a single dimension over which the fire spreads. However, managers may still choose how to allocate resources across directions of fire spread, allowing us to separately examine allocation decisions over space.

The timing of the model is as follows. In each period \( s \), there is a loss equal to \( h_{ls} \) if the fire has not yet been successfully extinguished in direction \( l \). The manager then chooses how much suppression effort to apply to the fire in each direction \( l \). Suppression effort, along with the fuels present in each direction, determine the probability that the fire will be extinguished. We define \( \xi_{ls} \) as a 1 \( \times \) \( L \) vector of state variables, where \( L \) is the total number of directions over which the fire can spread. Each element \( \xi_{ls} \) of \( \xi_{ls} \) is a binary variable indicating whether the fire has yet been extinguished in direction \( l \). Therefore, the law of motion for each element of \( \xi_{ls} \) is:

\[
\begin{align*}
\xi_{ls+1} &= \begin{cases} 
0 & \text{if } \xi_{ls} = 0 \text{ with prob. } 1 - f(e_{ls}, g_{ls}) \\
1 & \text{if } \xi_{ls} = 0 \text{ with prob. } f(e_{ls}, g_{ls}) \\
1 & \text{if } \xi_{ls} = 1 
\end{cases} 
\end{align*}
\quad (2)
\]

Finally, managers are subject to a budget constraint, which says that they cannot expend...
more than $M$ total effort over the course of the fire. We denote manager’s remaining budget at time $s$ as $m_s$, which has the law of motion $m_{s+1} = m_s - \sum_l e_{sl}$.

We can now write the fire manager’s problem as a dynamic program in discrete time. In each period $s$, the fire manager’s problem is to solve:

$$V_s(\xi_s, m_s) = \max_{\{e_{sl}\}_{l=1}^L} \left\{ \sum_{l=1}^L (1 - \xi_ls)h_ls \right\} + \beta E[V_{s+1}(\xi_{s+1}, m_{s+1}) | \xi_s, m_s]$$

subject to equation 2 and:

$$m_{s+1} = m_s - \sum_l e_{sl}. \quad (4)$$

Due to the ever increasing number of potential paths over which $\xi$ can evolve, this problem is not analytically tractable. However, this problem can be easily solved for fire spread in two directions using numerical grid search methods. An immediate next step in this project will be to use grid search methods to derive optimal suppression policy functions under a variety of scenarios. Estimating optimal policy functions for a variety of combinations of $h_{ls}$ and $g_{ls}$ functions will help us reach qualitative hypotheses regarding how we should expect managers to tradeoff levels of suppression effort within a wildfire incident when the fuel and values-at-risk profiles differ across directions of fire spread. Even without solving the model, however, it is clear that in principle the solution to the manager’s problem will be to allocate effort to equate marginal expected avoided losses across potential directions of fire spread.

### III. Empirical strategy

The previous section developed a theory of wildfire management in which fire managers minimize expected losses to homes. However, the theory left unspecified the way in which fire managers evaluate home losses. Whether fires are managed to minimize the number of homes lost, or whether they are managed to minimize losses in home value is an empirical question.

In this project, we hope to examine whether wildfire managers employ suppression strategies that are biased in favor of protecting higher value homes, or homes belonging to individuals with greater political connectedness. Ideally, we could test this by estimating the solution to the fire manager’s problem in equation 3. Unfortunately, we do not observe the evolution of wildfire incidents over time, so this is not possible. Moreover, we do not directly observe $\{e^s_{sl}\}$.

To overcome these empirical challenges, we make use of a fire simulation model, FARSITE, which is used by the USFS and other federal agencies for wildfire management and planning purposes. We use FARSITE to predict fire spread from a fire’s point of ignition using data on landscape cover and weather at the time of ignition. We argue that this predicted fire perimeter represents a likely outcome of fire spread were it not for intervention in the form suppression. In other words, FARSITE predicts the outcome of the incident if $e_{sl}$ were chosen to equal zero for all $s$ and $l$.

We combine fire simulation data with observed final fire perimeters. We interpret observed fire perimeters as the outcome of fire manager’s maximization of equation 3. That is, the perimeters are a result of managers’ choosing $e^*_s$ for every $s$ and $l$. Therefore, we interpret the difference between observed and simulated fire perimeters as a result of suppression effort and random error. We estimate the probability a home will burn as a function of the home’s assessed value ($h_{value}$), whether it would have been expected to burn in absence of suppression ($predict_{itf}$), and a series of co-

\[\text{In reality, not all homes within the final fire perimeter are destroyed or even damaged. However, since we do not observe which homes are destroyed, we refer to all homes whose footprints are within the final fire perimeter as having burned.}\]
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variates $X$:

$$h_{burn_{itf}} = \beta_1 h_{value_{it}} + \beta_2 predict_{itf} + \beta_3 (h_{value_{it}} \times predict_{itf}) + X'\beta + \epsilon_i$$

where $h_{burn_{itf}}$ is equal to 0 if home $i$ is within the realized perimeter of fire $f$ in year $t$ and 0 otherwise. Homes that ultimately lie within the actual fire perimeter of a fire may be at greater risk of burning for reasons that are endogenous to their value. For example, home owners may value living in forested areas or on the top of hills. Yet these characteristics of a home’s location make a home more likely to be burned if a fire starts nearby. For this reason, a simple regression of whether a home ends up within a fire’s final burn perimeter on home price is unlikely to be indicative of whether fire managers favor certain home owners in determining how to manage an incident.

Therefore, we use the FARSITE fire spread model to predict how a fire might have spread from its ignition point, given fuel conditions in the area and weather at the time of the ignition, were it not for intervention in the form of suppression. We control for whether a home is within the predicted fire boundary and test whether higher value homes within the predicted fire boundary are less likely to burn than homes with lower value.

Managers attempt to minimize total losses to homes over the course of a fire. When a fire encroaches on one home, it likely also threatens the homes nearby, therefore we include in $X$ a variety of measures of average home value within the neighborhood of home $i$. Furthermore, as the conceptual model developed in section II makes clear, the final fire boundary will be the result of fire managers’ solution to a dynamic optimization problem. Fire managers must not only be concerned with other homes in the neighborhood of home $i$, they must be concerned with potential home losses in a given direction of fire spread if the fire continues to spread in that direction. Therefore we also include in $X$ controls for the value of homes in neighborhoods both nearer to and farther from the ignition point than the neighborhood of home $i$.

IV. Data

Data for this project fall into three broad categories: housing data, observed fire ignitions and fire perimeter data, and data that are used to simulate fire perimeters in the absence of suppression. Housing data come from Data Quick Information Systems, used under a license agreement with the Duke Department of Economics. The Data Quick data set includes variables on assessed home values and home characteristics, in addition to locations of homes. We also use data from the University of Wisconsin SILVIS lab regarding the extent of wildland urban interface in the U.S. (Radeloff et al., 2005), based on the definition of WUI given in the federal register (USDA and DOI, 2001).

Figure 2: Map of fire subsample and weather stations
Table 1: Rates of fuel reduction by land cover type

<table>
<thead>
<tr>
<th>Reporting agency</th>
<th>All California Mean</th>
<th>All California Count</th>
<th>Subsample Mean</th>
<th>Subsample Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bureau of Indian Affairs</td>
<td>0.01</td>
<td>105,777</td>
<td>0.01</td>
<td>573</td>
</tr>
<tr>
<td>Bureau of Land Management</td>
<td>0.13</td>
<td>105,777</td>
<td>0.23</td>
<td>573</td>
</tr>
<tr>
<td>Forest Service</td>
<td>0.22</td>
<td>105,777</td>
<td>0.45</td>
<td>573</td>
</tr>
<tr>
<td>Fish and Wildlife Service</td>
<td>0.03</td>
<td>105,777</td>
<td>0.01</td>
<td>573</td>
</tr>
<tr>
<td>National Park Service</td>
<td>0.02</td>
<td>105,777</td>
<td>0.05</td>
<td>573</td>
</tr>
<tr>
<td>State, County, or Local</td>
<td>0.56</td>
<td>105,777</td>
<td>0.24</td>
<td>573</td>
</tr>
<tr>
<td>Tribe</td>
<td>0.02</td>
<td>105,777</td>
<td>0.00</td>
<td>573</td>
</tr>
<tr>
<td>Other</td>
<td>0.00</td>
<td>105,777</td>
<td>0.00</td>
<td>573</td>
</tr>
<tr>
<td>Total</td>
<td>0.98</td>
<td>105,777</td>
<td>1.00</td>
<td>573</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total fire size (acres)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0 to 0.25 acres</td>
<td>0.50</td>
<td>105,777</td>
<td>0.01</td>
<td>573</td>
</tr>
<tr>
<td>0.25 to 10 acres</td>
<td>0.43</td>
<td>105,777</td>
<td>0.01</td>
<td>573</td>
</tr>
<tr>
<td>10 to 100 acres</td>
<td>0.05</td>
<td>105,777</td>
<td>0.02</td>
<td>573</td>
</tr>
<tr>
<td>100 to 300 acres</td>
<td>0.01</td>
<td>105,777</td>
<td>0.10</td>
<td>573</td>
</tr>
<tr>
<td>300 to 1000 acres</td>
<td>0.01</td>
<td>105,777</td>
<td>0.54</td>
<td>573</td>
</tr>
<tr>
<td>1000 to 5000 acres</td>
<td>0.00</td>
<td>105,777</td>
<td>0.33</td>
<td>573</td>
</tr>
<tr>
<td>5000 or more acres</td>
<td>0.00</td>
<td>105,777</td>
<td>0.00</td>
<td>573</td>
</tr>
<tr>
<td>Total</td>
<td>1.00</td>
<td>105,777</td>
<td>1.00</td>
<td>573</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time to containment</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0 days</td>
<td>0.82</td>
<td>51,149</td>
<td>0.07</td>
<td>458</td>
</tr>
<tr>
<td>1 day</td>
<td>0.11</td>
<td>51,149</td>
<td>0.07</td>
<td>458</td>
</tr>
<tr>
<td>2 to 5 days*</td>
<td>0.04</td>
<td>51,149</td>
<td>0.27</td>
<td>458</td>
</tr>
<tr>
<td>5 to 10 days</td>
<td>0.01</td>
<td>51,149</td>
<td>0.21</td>
<td>458</td>
</tr>
<tr>
<td>11 to 20 days</td>
<td>0.01</td>
<td>51,149</td>
<td>0.13</td>
<td>458</td>
</tr>
<tr>
<td>More than 20 days</td>
<td>0.01</td>
<td>51,149</td>
<td>0.26</td>
<td>458</td>
</tr>
<tr>
<td>Total</td>
<td>1.00</td>
<td>51,149</td>
<td>1.00</td>
<td>458</td>
</tr>
</tbody>
</table>

Note: The first two columns include all fire records for fires within the state of California in years 2000-2013 as reported in Short (2015). The second two columns include only those fires with non-missing MTBS IDs and within 10 kilometers from census blocks classified as wildland urban interface by Radeloff et al. (2005).

Data on observed fire ignitions come from Short (2015), who compiled a comprehensive data set of wildfires within the United States from 1993 to 2013 from a variety of federal, state, and local sources. Fires in the database include a latitude and longitude, which are meant to represent each fire’s point of origin, as well as a variety of other details regarding each fire incident. Data on observed fire perimeters come from the Monitoring Trends in Burn Severity (MTBS) project (MTBS, 2014). Since 1984, the MTBS has used Landsat satellite imagery to map the geographic extent, as well as the severity, of all fires greater than 1000 acres in size in the western U.S. Table 1

4In addition, MTBS maps fires larger than 500 acres in
Figure 3: Predicted wildfire spread, simulated using FARSITE

summarizes fire occurrence data for fire ignitions in California from 1993 to 2013. The first two columns provide summary statistics for all California wildfire incidents, whereas in the final two columns the sample is restricted to those fires with non-missing MTBS ideas that are within 10 km of a wildland urban interface Census block. Since the subsample is restricted to fires meeting MTBS mapping requirements, and to fires that were in relatively close proximity to the wildland urban interface, it is not a surprise that fires in the subsample are larger size in the eastern U.S., and all fires that occur within the boundaries of National Park Service units. and longer in duration. Additionally, the subsample includes a higher proportion of U.S. Forest Service and Bureau of Land Management fires and fewer state, county, and local fires. The subsample is the sample of fires we are interested in for the purpose of our analysis.

For each of the fires in the subsample, we use the USFS FARSITE fire spread model [Finney 1998] to simulate how each fire might have spread from its ignition point were it not for the influence of suppression. The USFS, as well as other federal agencies and independent researchers have developed a large number of models that can be used to simulate the spread
Table 2: Assessed housing values by position relative to simulated and actual fire perimeters

<table>
<thead>
<tr>
<th></th>
<th>Inside simulated perimeter</th>
<th>Outside simulated perimeter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean home value</td>
<td>Number of homes (count)</td>
</tr>
<tr>
<td>Inside actual perimeter</td>
<td>$149,817</td>
<td>572</td>
</tr>
<tr>
<td>Outside actual perimeter</td>
<td>$258,661</td>
<td>1,610</td>
</tr>
</tbody>
</table>

Note: Assessed housing values from DataQuick Information Systems.

of fire across a landscape. Models developed and in use by federal land management agencies include FlamMap, BehavePlus, and FSPro. Federal agencies use these models for a variety of purposes including risk assessments, fuels reduction treatment planning, and planning suppression activities within the context of an individual wildfire incident. Relative to other fire simulation models available, FARSITE has the advantage of allowing for input of a variable weather stream, whereas other models assume weather is constant over the course of a fire.

FARSITE takes as inputs landscape data, including data on topography and fuel characteristics, data on weather and wind, an ignition point or perimeter, and a variety of parameters chosen by the analyst. Landscape data are taken from the Landfire project, a cooperative project between the U.S. Forest Service and Department of Interior (Rollins, 2008). These data include topographical GIS layers, as well as layers describing vegetation cover, density, height, and type. Weather data are taken from the Western Regional Climate Center, which provides historical weather data, including hourly temperature, relative humidity, precipitation, and average wind speed and directions for Remote Automatic Weather Stations (RAWS) throughout California. Stations were established at various points over time; some date to as far back as 1990, though many were established after 2000. Ignition points are taken from Short (2015). Figure 2 shows the locations of fire ignitions used in this paper, as well as the locations of weather stations from which weather data are drawn.

Using these inputs, we used FARSITE to model the spread of fires in our dataset. FARSITE outputs predicted fire perimeters at time intervals chosen by the user. We output bi-hourly fire perimeters. Fire spread models are generally not well-suited to predicting when a fire will stop; therefore, we also determined the number of periods over which the fire would spread. We calculated the number of days between each fire’s discovery and date of containment and allowed simulated fires to spread for an equal number of days. Figure 3 provides an example of output from the FARSITE model for two fires in southern California.

V. Progress and future work

Presently, I have run FARSITE fire simulations for a small subset of wildfires within the fire sample. Example output from this set of fire simulations is provided in figure 3. In order to provide an initial test of this paper’s central hypothesis, I combined the small subset of completed wildfire simulations with data on housing values within the realized and simulated fire perimeters. Summary statistics from this comparison are provided in table 2. Among homes that are predicted to burn, homes that are in the actual burn perimeter are

5Presently, only a small set of trial fires have been simulated. Further work to correctly set parameters and address missing data problems will be needed before the full set of wildfires can be simulated.
higher value than homes inside the actual burn perimeter. Though this comparison relies on a very small sample size and does not account for possible confounding factors, it suggests that it is possible that managers may favor protection of high value homes when implementing fire suppression strategies.

I am making progress debugging the scripts to run the full set of fire simulations needed to complete the data set for this project. Before running the final set of simulations, I will also need to carefully choose FARSITE parameter values in order to estimate accurate fire simulation models. This will be done with the help of an experienced FARSITE user from the U.S. Forest Service in Santa Barbara. Finally, I will merge fire simulation data with actual fire perimeters and housing data, and estimate models based on the model described in section III.

REFERENCES


