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Priorities and Effectiveness in Wildfire Management: Evidence from Fire Spread in the Western United States

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Working Paper 20-21
December 2020

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Abstract

Within the western United States, wildfire activity and costs of fighting wildfires have increased substantially over the past several decades. Yet surprisingly little is known about the effectiveness of wildfire suppression on large fires or about how wildfire incident managers use their significant discretion to prioritize resources threatened in wildfire incidents. We investigate priorities and effectiveness of wildfire suppression using a novel empirical strategy that compares 1,500 historical fire perimeters with the spatial distribution of assets at risk to identify determinants of wildfire suppression efforts. We find that fires are more likely to stop spreading as they approach homes, particularly when those homes are of higher value. This effect of threatened assets persists after controlling for physical factors (fuels, landscape, and weather) using outputs from a state-of-the-art wildfire simulation tool, and the probability that fire spread will be halted is affected by characteristics of homes 1–2 km from a fire's edge. Our results provide evidence that wildfire suppression can substantively affect outcomes from wildfires but that some groups may benefit more from wildfire management than others.

Keywords: Natural disasters, Wildfire, Spatial-dynamic resources, Adaptation, Duration

JEL Codes: H41 (Public goods), Q28 (Renewable resources and conservation: Government policy), Q54 (Environmental economics: Natural disasters and their management)

1. Introduction

Over the past several decades, wildfire activity in the western United States has dramatically increased, highlighted by the recent rash of devastating fires that have struck California, including 2018's Camp, Carr, and Mendocino Complex fires and 2017's wine country fires. Fires can become large disaster events that kill firefighters and civilians, destroy homes, and significantly impair air quality; the Camp Fire, for example, was the world's costliest natural disaster in 2018 (Munich Re, 2019). As such, large fires prompt a considerable government response. Wildfire suppression, defined as management responses intended to put fires out or minimize their spread, costs the federal government approximately $2 billion each year, with states contributing another $1 billion (National Interagency Fire Center, 2020; Cook and Becker, 2017).[1] Most of this spending goes toward suppression of large fires (Calkin et al., 2005). Federal agencies employ more than 34,000 wildland firefighters annually (Butler et al., 2017), and hundreds or thousands of firefighters from federal, state, and local agencies respond to large wildfire incidents.

Despite the level of resources committed to battling large fires, surprisingly little is known about the effectiveness of suppression spending on large wildfires or about how wildfire managers prioritize suppression efforts. It is widely believed that fire suppression has been highly effective when firefighters have been able to extinguish fires early; during 1995–2005, more than 97% of US wildland fires were extinguished almost immediately while they were very small (Stephens and Ruth, 2005), and area burned in the western United States declined dramatically in the middle of the twentieth century during a period of increasingly aggressive fire suppression (Littell et al., 2009). However, the effectiveness of fire suppression efforts in combating large wildfires is less well understood. While empirical evidence indicates that proximity to homes is a primary predictor of federal and state agency fire suppression effort, few studies evaluate prioritization of wildfire suppression in relation to the number and value of homes and the demographic groups affected.

In this paper, we estimate the effect on wildfire spread of wildfire suppression on behalf of threatened resources. Consistent with prior research, our results indicate that preventing damage to homes is a primary motivator of suppression effort. We find evidence that fire managers commit greater effort to combat the spread of fires toward high-value homes, as well as weak evidence that they preferentially protect wealthier neighborhoods. Further, our results indicate that this effort can be at least moderately effective in stopping fire spread. Therefore, our evidence indicates that decisions made by fire managers favor particular groups and materially affect outcomes for those groups.

[1] For comparison, annual US spending on all natural disasters averaged $27.7 billion between 2005 and 2014 (US GAO, 2016).

Many empirical wildfire suppression studies have used fire-level regressions to compare suppression costs across fires. For example, previous studies have found that large wildfires are responsible for the majority of suppression spending (Calkin et al., 2005), and fires that require heavy use of aircraft have low rates of containment (Calkin et al., 2014). It is difficult to interpret these results causally, however, because suppression effort is chosen endogenously to the threat a fire poses; regressions of suppression spending on fire size are expected to be biased upward and may estimate a positive correlation between spending and size. Other studies have examined differences in suppression spending due to proximity to homes (Gebert et al., 2007; Liang et al., 2008; Baylis and Boomhower, 2019). These studies find that suppression effort increases with proximity to homes but generally do not consider differences in suppression effort across numbers and values of homes at risk or across demographic groups at risk.[2] A disadvantage of these studies, however, is that because they estimate a fire-level regression, they are limited in their ability to control for landscape characteristics, such as topography and fuels, that may be correlated with both home values and suppression spending. Commonly, landscape features are represented with a single value or summary statistic (e.g., fuels at the fire ignition location).

Our strategy is distinct from previous studies of wildfire suppression in that we draw inferences regarding fire suppression effort and priorities from observed patterns of wildfire spread across the landscape. First, we develop a simple spatial-dynamic theory of wildfire suppression decisionmaking that relates decisions over the allocation of suppression resources to the distribution of assets at risk on the landscape. Motivated by this theory, we use a novel empirical "spatial duration model" to compare the final extent of fire spread for 1,503 western wildfires with the spatial distribution of assets at risk. We find that fires are more likely to stop spreading as they approach homes, and the likelihood that the fire will stop spreading increases as the number and especially the value of homes increase.

Controlling for the effects of physical and topographic factors on fire spread allows us to attribute differences in the likelihood that the fire stops spreading to the suppression effort on behalf of the value of assets at risk. We do this using a fire simulation model known as Minimum Travel Time (MTT), which was developed by the US Forest Service and is used in the management of wildfire incidents. MTT integrates spatial data on physical features as well as time-varying data on vegetation and winds to predict wildfire behavior on the landscape. Conditioning on predictions of wildfire behavior allows us to contrast fire spread across locations where wildfire behavior is similar but assets at risk are different, thereby attributing the effects of assets at risk to suppression effort on behalf of those assets.

[2] One exception is Baylis and Boomhower (2019), who find that the presence of homes near a fire increases suppression costs but that the effect declines as the number of homes increases. Using data on home transaction values, they find that, on a per-home basis, suppression spending is greatest for low-value homes.

The approach resolves several challenges in the empirical analysis of wildfire suppression decisionmaking. Detailed spatiotemporal data regarding within-fire allocation of suppression efforts, including deployment of firefighter teams, are generally unavailable. Our approach allows us to draw inferences regarding allocation of suppression efforts without explicit spatiotemporal data on resource use. Further, this approach provides an alternative means of assessing the effectiveness of suppression efforts in large wildfire incidents that avoids endogeneity concerns associated with regressing costs on fire size. Wildfire management requires solving highly complex spatial-dynamic optimization problems. Our approach accounts for the spatial-dynamic aspects of the fire manager's decision problem in a tractable manner, allowing us to account for factors that affect spread at a fire's current extent, rather than just at its ignition point.

This paper makes contributions to several literatures. First, it contributes to the literature on natural disasters and environmental justice. Since the 1970s, academics have studied differences in exposure to environmental amenities and risks (e.g., Brown, 1995; Ringquist, 2005). Following Hurricane Katrina, researchers gave increased attention to differences across groups in exposure to risk of disasters, primarily floods (e.g., Cutter, 2012; Maantay and Maroko, 2009; Montgomery and Chakraborty, 2015). However, little attention has been paid to the potential role of government disaster response in exacerbating inequality in disaster outcomes, despite research suggesting that government disaster responses are frequently politically motivated (e.g., Healy and Malhotra, 2009; Achen and Bartels, 2004). In the wildfire context, Donovan et al. (2011) found that firefighters are more likely to make use of high-visibility aircraft in incidents that receive greater news coverage. Government plays an important role in responding to natural disasters, and particularly in influencing the extent of wildfires. Therefore, it is important to understand the priorities and motivations of government wildfire managers and how these affect wildfire outcomes.

We also contribute to the literature on spatial-dynamic natural resource management. This paper is among the first to empirically examine management of spatial-dynamic resources in a way that explicitly accounts for spatial dynamics. Much of the previous literature on spatial-dynamic resource management has been theoretical in nature because of the difficulty associated with estimating high-dimensional spatial-dynamic models. Previous studies have developed theories of optimal harvesting within a spatially connected fishery (Costello and Polasky, 2008), optimal control of invasive species (Epanchin-Niell and Wilen, 2012), and optimal patterns of fuel management under wildfire risk (Konoshima et al., 2010). However, few studies have empirically examined forward-looking resource management in a spatial context.[3] In the wildfire context, Bayham and Yoder (2020) make use of detailed wildfire panel data to evaluate resource allocation within wildfire incidents, but no previous empirical studies have evaluated management

[3] For example, Huang and Smith (2014) model the dynamic decision by fisherman to fish or not, but not the decision of where to fish.

of individual fire incidents in an explicitly spatial-dynamic manner.

2. The wildfire suppression decision environment

Fire managers operate within a highly complex decisionmaking environment with respect to both the institutional setting and the resource they are tasked with managing. Fires are spatial-dynamic phenomena, which may spread quickly across landscapes comprising multiple landowners, both private and public. Wildfires are also infrequent: the likelihood that a plot of land burns in a given year is usually low. To minimize fixed costs associated with maintaining fire management resources, a system has evolved in which responsibilities and resources are shared among landowners and land management agencies. On unincorporated private lands, landowners generally yield responsibility for fire suppression to state agencies (e.g., Cal Fire in California). Federal and state land management agencies are responsible for managing fires that burn on their lands, but they frequently share resources to do so effectively and at lower cost. Because of the cooperative interagency nature of wildfire management, federal, state, local, and tribal governments have collaborated to develop a national wildfire policy that provides fire managers with consistent goals and guidelines for fire management (Wildland Fire Leadership Council, 2014). However, while the national strategy provides guiding principles for wildfire suppression, each incident presents unique challenges, and no national policy document can prescribe a blueprint for management of every incident. Even where national forests or other local units have developed local fire policies or plans, wildfire incidents will vary in firefighting resources available, weather conditions, and specific assets threatened. The emergency nature of wildfires requires that fire managers be allowed a high degree of discretion to make strategic decisions to minimize losses.

Fire suppression proceeds in two phases. Upon initially discovering a fire, the nearest fire management authority will usually attempt to quickly extinguish it in what is known as the initial attack.[4] When fires escape managers' initial attempts at containment, fire suppression enters extended attack. During extended attack, fire managers rely on three sets of tactics: direct attack, aerial attack, and indirect attack (NWCG, 2017). Direct attack includes tactics in which firefighters directly apply treatment to burning fuel. Direct attack tactics are typically used when fires are relatively small, which enables firefighters to work close to burning material and physically smother the flames or apply water or chemical retardant. Aerial attack involves applying water or chemical fire retardants from the air using helicopters or fixed-wing aircraft. Indirect attack includes fire sup-

[4] Even where federal lands intermingle with state and private lands, land management agencies generally have agreements that allow the nearest fire management authority to respond to an ignition, regardless of the specific jurisdiction in which it occurs.

pression activities that take place at some distance from the perimeter of the actively burning fire. For example, fire managers frequently work in advance of a fire's spread to construct fuel breaks, areas where burnable material has been removed to stop a fire's spread. Fuel breaks can be constructed using hand tools or heavy equipment, or by "backburning," which involves taking advantage of favorable wind conditions and setting fire to fuels in the main fire's path, thus creating a fuel break. Fire managers can also take advantage of preexisting fuel breaks, such as roads.

In choosing how to deploy suppression resources, fire managers face a set of loosely defined incentives. Managers do not own the assets they are charged with protecting. Therefore, their decisionmaking is subject to bureaucratic incentives including intrinsic motivations, pressure from politicians and stakeholder groups, and concerns over the career or personal liability consequences of their decisions. Similarly, fire managers are not directly responsible for the financial costs of their strategic decisions. Indeed, even the agency employing fire managers may not face direct opportunity costs of suppression spending since suppression is frequently funded out of emergency funds rather than through appropriations (Donovan and Brown, 2005; Taylor, 2019). While incentives facing fire managers are poorly defined, we follow much of the fire management literature in assuming that fire managers simply choose strategies to minimize the sum of suppression costs and wildfire damages (Sparhawk, 1925; Donovan and Rideout, 2003). Importantly, though, we allow weights to be determined empirically, and we avoid making assumptions about how bureaucratic incentives bear on the relative importance managers give to costs and protection of various assets.

Finally, the decision problem that fire managers face is complicated by the fact that, as noted previously, wildfires are a fundamentally spatial-dynamic phenomenon. To manage them effectively, fire managers must be forward-looking, anticipating where and when a fire might spread and what resources it might put at risk. Their expectations are guided by experience, knowledge of fire behavior and weather, and sophisticated wildfire simulation software, including FARSITE (Finney, 1998) and FSPro (Finney et al., 2011), developed to aid fire management decisionmaking. Wildfire simulation models integrate data on topography, weather, and fuels within a physical model of fire behavior to predict how these elements come together to influence wildfire spread. These predictions provide fire managers with information about which portions of the landscape face the greatest threat. In the empirical model, we use fire simulation models to help control for effects of spatial variation in fuels and topography on wildfire spread.

3. Theory

This section develops a theoretical model of the decision problem facing fire managers. The model motivates the empirical analysis of factors affecting fire spread in two ways. First, it emphasizes the spatial-dynamic nature of the fire manager's problem and the role that uncertainty plays. Fire spreads in multiple directions over space and time, and an increased suppression effort does not guarantee a fire's extinction in a given direction of spread. Therefore, how managers allocate effort across directions of spread will depend on the spatial distribution of at-risk assets and the manager's assessment of the likelihood that the fire will reach those assets if the fire is not stopped at its current point of spread. Second, the model provides an implicit policy function describing the fire manager's optimal allocation of suppression efforts, which motivates the specification of the empirical model developed in the next section.

To begin, we allow for fire spread in multiple discrete directions, indexed by ℓ, from its ignition point. To avoid tracing fire spread across both distance and time, we assume that the fire burns at unit speed in all directions. Therefore, at time $t = s$, the fire is distance s from its ignition point in each direction ℓ, conditional on it not yet having been extinguished in that direction. Values at risk in location $s\ell$ are described by the vector $\mathbf{x}_{s\ell}$. If the fire burns to distance s in direction ℓ, the fire destroys assets present at that location, and fire managers lose utility $u(\mathbf{x}_{s\ell})$. Ignitable fuels at distance s in direction ℓ are given by $r_{s\ell}$. At each location $s\ell$, the probability the fire is extinguished is a function of both fuels in that location and effort $e_{s\ell}$ expended toward suppressing the fire. Therefore, we write the probability that the fire is extinguished at point s, conditional on reaching point s, as $\lambda(e_{s\ell}, r_{s\ell})$, and we assume that $\lambda(\cdot)$ is decreasing in fuels and increasing in effort. Additionally, we assume that the marginal effect of effort on extinction probability is decreasing in fuels. The fire manager allocates effort across directions-of-spread ℓ to minimize expected losses across all directions. We define $\boldsymbol{y}_s$ 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 $y_{s\ell}$ of $\boldsymbol{y}_s$ is a binary variable equal to zero if the fire has not yet been extinguished in direction ℓ at distance s. Therefore, the law of motion for each element of $\boldsymbol{y}_s$ is

$$y_{s+1,\ell} = \begin{cases} 0 \text{ with prob. } 1 - \lambda(e_{s\ell}, r_{s\ell}) \text{ if } y_{s\ell} = 0 \\ 1 \text{ with prob. } \lambda(e_{s\ell}, r_{s\ell}) \text{ if } y_{s\ell} = 0 \\ 1 \text{ if } y_{s\ell} = 1 \end{cases} \tag{1}$$

Managers are subject to a budget constraint, which says that they cannot expend more than $\bar{b}$ total effort over the course of the fire. The remaining budget at time s is denoted as b_s and evolves according to $b_{s+1} = b_s - \sum_{\ell=1}^{L} c(\mathbf{z}_{s\ell})e_{s\ell}$, where $b_0 = \bar{b}$ and $\mathbf{z}_{s\ell}$ is a vector of location-specific characteristics that affect marginal costs of suppression at location $s\ell$.

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

$$V_s(\boldsymbol{y}_{s\ell}, b_s) = \max_{e_s} -\sum_{\ell=1}^{L}(1 - y_{s\ell})u(\mathbf{x}_{s\ell}) + \beta_y\big[V_{s+1}(\boldsymbol{y}_{s+1}, b_{s+1})|\boldsymbol{e}_s\big] \tag{2}$$

subject to equation 1, $b_{s+1} \geq 0$, and the law of motion for b_s. To solve this problem, the manager will choose $\mathbf{e}_s^*$ such that

$$\lambda_e(e_{s\ell}^*, r_{s\ell})\Big[\frac{\partial V_{s+1}}{\partial y_{s+1,\ell}}(\mathbf{e}_s^*)\Big] = c(\mathbf{z}_{s\ell})\Big[\frac{\partial V_{s+1}}{\partial b_{s+1}}\Big] \tag{3}$$

for all directions ℓ. Although it is not possible to find a closed-form analytic solution to this problem, this condition nevertheless provides intuition regarding a manager's optimal allocation of effort across directions. The condition says that managers should choose effort to equate marginal benefits with marginal costs across all directions of spread. The left-hand side of the condition represents the marginal benefit of suppression. Effort affects the continuation value V_{s+1} through its effects on extinction probability and expected avoided losses $u(\mathbf{x}_{\ell s})$. For directions of spread with greater assets, increasing probability of extinction before the fire reaches those assets may provide greater benefits. However, because marginal effects of suppression effort on extinction probability are decreasing in fuels r, the fire manager should also adopt a landscape-level perspective and allocate effort across directions at appropriate and opportune moments. The right-hand side of equation 3 represents marginal costs of the suppression effort. Increases in effort draw down the remaining budget and thus decrease the continuation value.

This model abstracts from reality in several ways. In reality, managers can take indirect actions such as building a fuel break in advance of a fire's spread. While the model explicitly allows managers to take action only at the fire's current point of spread, indirect attacks are considered implicitly by allowing managers to "save" against their budget b. If the marginal effect of effort on the probability of extinction increases over some range of efforts, it may be worthwhile for the fire manager to wait to spend large portions of the fire management budget at once. More significantly, the model requires that fires spread linearly over independent directions of spread. In reality, fires spread stochastically across a two-dimensional landscape. Unfortunately, realistically accounting for the nonlinearity of fire spread would yield a high-dimensional spatial-dynamic model. Theoretical solutions to such a model would be numerically as well as analytically intractable, and empirically evaluating such a model would be impractical. Simplifying the manager's problem in this way significantly reduces the dimensionality of the problem while retaining insights regarding its spatial-dynamic nature.

4. Empirical model

4.1 Fire spread distance as duration

To estimate the effects of natural factors and the fire manager's suppression effort on fire extinction probability, while accounting for the spatial-dynamic nature of the fire manager's decision problem described in section 3, we adapt methods from duration analysis to a spatial setting. Consider a fire burning in a single direction. At any point along the fire's path of spread, there is some probability that the fire will stop spreading. In the language of duration analysis, the fire "exits the state." Therefore, we draw a parallel between fire spread distances and durations and apply tools from duration analysis. The extinction probability, or the probability that a fire is extinguished at distance s from its ignition point conditional on it not yet having been extinguished, corresponds to a hazard rate. We model the extinction probability as depending on natural characteristics (r_s) and fire suppression effort (e_s), both of which vary over space. Spatially varying data on within-fire allocation of suppression effort are unavailable. Therefore, motivated by the theoretical model described in the previous section, we use observable factors that affect the costs and benefits of fire suppression in a given location as a proxy for effort.

We write the fire extinction probability as $\lambda(s, e_s, r_s; \theta)$, where θ is a vector of parameters. Using standard derivations from duration analysis, the cumulative distribution function of fire spread distance can be written as

$$F(s) = 1 - \exp\big[-\int_0^s \lambda(s, e_s, r_s; \theta) ds\big]. \tag{4}$$

Since fires potentially spread in 360 degrees from their points of origin, we divide the landscape around each ignition into L directions of spread, where directions of spread are indexed by ℓ. We then divide each direction of spread into distance intervals, where each interval m defines a grid cell spanning the distance $(a_{m-1,\ell}, a_{m,\ell}]$ in direction ℓ for $m = 1, \ldots, M$. We define $y_{m\ell}$ as equal to 1 if the fire stops burning within $a_{m-1,\ell}$ and $a_{m,\ell}$ kilometers from the ignition point and 0 otherwise. Each direction of spread is observed up to the interval at which it stops burning, which is denoted M_ℓ, or until the maximum distance M is reached. If the fire continues to burn in direction ℓ upon reaching distance M, the fire-direction observation is right-censored.

We apply grouped duration data methods (e.g., Sueyoshi, 1995) because our measure of fire spread distance is observed within discrete distance intervals. Using equation 4, the probability that a fire is observed to stop burning within the interval $(a_{m-1,\ell}, a_{m,\ell}]$ along direction of spread ℓ can be written as follows:

$$(y_{m\ell} = 1 | y_{m-1,\ell} = 0, m \leq M) = 1 - \exp\big[-\int_{a_{m-1,\ell}}^{a_{m\ell}} \lambda(s, e_\ell, r_{s\ell}; \theta)\, ds\big]. \tag{5}$$

Under the assumption that factors affecting extinction probability are constant within interval $m\ell$, we define $\mathbf{w}_{m\ell}$ to be a vector describing e_s and r_s within the interval. We then define $\alpha_m(\mathbf{w}_{m\ell};\theta) = \text{exp}\left[-\int_{a_{m-1}}^{a_m} \lambda(s, e_s, r_s; \theta)ds\right]$, the probability that a fire is halted within $(m-1, m]$. We assume that conditional on $\mathbf{w}_{m\ell}$, the probability that the fire is extinguished is independent across intervals within a single direction of spread. Then the likelihood function for a single fire-direction observation can be written as

$$\mathcal{L}_\ell(\theta|M_\ell) = \big(1 - \alpha_m(\mathbf{w}_{m\ell};\theta)\big) \prod_{m=1}^{M_{\ell-1}} \alpha_m(\mathbf{w}_{m\ell};\theta), \tag{6}$$

where the first term represents the probability that the fire will stop burning within interval M_ℓ, and the second term represents the probability that the fire continues to burn within each of the intervals prior to interval M_ℓ. Further, for the purposes of deriving the overall likelihood function, we maintain the assumptions that, conditional on $\mathbf{w}_{m\ell}$, $\alpha_m(\mathbf{w}_{m\ell};\theta)$ is independent across fires and directions of spread. This latter assumption is unlikely to hold in reality. For example, a fire that spreads a great distance to the northeast is also more likely to spread a great distance to the north-northeast. In section 4.3, we will discuss how we test the model's robustness to nonindependence among fire spread directions. For now, however, we maintain this assumption and use it to write the overall likelihood function over L directions of spread and K fires as

$$\mathcal{L} = \prod_{k=1}^{K}\prod_{\ell=1}^{L}\prod_{m=1}^{M_\ell} \big(1 - \alpha_m(\mathbf{w}_{m\ell};\theta)\big)^{y_{m\ell k}} \alpha_m(\mathbf{w}_{m\ell};\theta)^{(1-y_{m\ell k})}. \tag{7}$$

This likelihood function is the same form as the likelihood function of a standard binary response model, where the particular binary response model to be estimated depends on the specification of the probability $\lambda(\cdot)$ (Jenkins, 1995; Sueyoshi, 1995).

4.2 Specification of spread-distance model

To estimate equation 7, we assume that the extinction probability is of the form

$$\lambda(s, e_s, r_s; \theta) = \text{exp}\left(e_{m\ell} + r_{m\ell}\right)\lambda_0(s), \tag{8}$$

where $e_{m\ell}$ is a variable summarizing effort and $r_{m\ell}$ is a variable summarizing the effects of landscape and weather conditions on extinction probability. That is, we assume that the extinction probability takes the form of a standard proportional hazard model. In allowing λ_0 to vary by distance s, the proportional hazard model allows for duration dependence. This is important in modeling fire spread distance because fires that grow large are more likely to continue to burn. Letting $\delta_m = \text{ln} \int_{a_{m-1}}^{a_m} \lambda_v dv$ and using equation 5, we can write the extinction probability as

$$\alpha_m(\mathbf{w}_m;\theta) = \text{exp}\left[-\int_{a_{m-1}}^{a_m} \text{exp}(e_{m\ell} + r_{m\ell} + \gamma_m)\, dv\right] \equiv F\big(e_{m\ell} + r_{m\ell} + \delta_m\big). \tag{9}$$

This is the cumulative distribution function of the complementary log-log distribution, implying that a proportional hazard model corresponds to an easily estimated complementary log-log model with distance-interval fixed effects. Distance-interval fixed effects account for duration dependence in a nonparametric manner that makes no assumptions regarding the form of duration dependence.

According to the theory developed in section 3, effort at a given location depends on the costs of suppression as well as the benefits. Benefits are a function of assets protected by suppression, including assets at the fire's current location and, potentially, assets located farther in the direction of spread that are protected by suppression of the fire at that location. Costs include the costs of fighting the fire at its current location and expected costs of suppression if the fire is allowed to spread. Therefore, we write effort as $e_{m\ell} = \sum_{\nu=0}^{\bar{\nu}} \beta^{\nu} \mathbf{x}_{m+\nu,\ell} + \gamma^{\nu} \mathbf{z}_{m+\nu,\ell}$, where benefits and costs of suppression in location $m\ell$ are described by vectors $\mathbf{x}_{m\ell}$ of assets at risk and $\mathbf{z}_{m\ell}$ of factors affecting costs. Suppression effort is specified as a function of "spatial leads" of benefits and costs of suppression up to $\bar{\nu}$ cells away.[5]

A variety of physical variables—including topography, forest conditions, fuel moisture, wind, and temperature—can interact in complex ways to affect fire spread. To account for the combined effects of these factors, we rely on outputs from a US Forest Service fire simulation tool. The simulation tool, which we will describe in greater detail in the following section, uses observed conditions at the time of a fire's ignition to predict how a fire will spread over space. Specifically, it predicts landscape-wide surfaces of fire arrival times and fire intensities, were the fire allowed to spread uncontained. We denote the time of the fire's arrival at location $m\ell$ as $T_{m\ell}$ and use the difference $\Delta T = T_{m\ell} - T_{m-1,\ell}$ to account for the combined effects of physical factors on fire extinction. Since fire extinction may only become more likely once the rate of spread has slowed sufficiently, we allow ΔT to influence the complementary log-log index function through the nonlinear function $r(\mathbf{v}_{m\ell})$, where $\mathbf{v}_{m\ell}$ is a vector of variables, including output from a fire simulation tool, that describe combined effects of physical factors on fire spread across the landscape. In summary, the complementary log-log distribution we estimate is

$$F\Big(\sum_{\nu=0}^{\bar{\nu}} \{\beta^{\nu} \mathbf{x}_{m+\nu,\ell} + \gamma^{\nu} \mathbf{z}_{m+\nu,\ell}\} + r(\mathbf{v}_{m\ell}) + \delta_m\Big). \tag{10}$$

[5] In the preferred specification, we also allow suppression effort to depend on assets and factors affecting costs in cell $m-1, \ell$. That is, we let $\nu_0 = -1$ and include a single spatial lag. We will describe why this is reasonable after discussing the setup of the data.

4.3 Identification and inference

The key identifying assumption in this paper is that, after controlling for observed natural factors that affect fire spread, random factors that affect fire spread are uncorrelated with effort. A threat to identification would exist if there were omitted factors that affected extinction probability and were correlated with effort. For example, population within an interval might be correlated with an area's tendency to burn, even after controlling for natural factors. Therefore, identification of the effects of assets at risk on suppression effort rests in large part on how well the simulated fire-spread variables account for the landscape's tendency to burn.

As indicated earlier, the assumption that extinction probabilities are independent across directions of spread is likely false. As derivation of equation 7 requires the independence assumption, violations of independence may bias the coefficient and standard error estimates. We adopt several strategies to test the sensitivity of results to violations of this assumption. First, we estimate a linear probability model and compare the resulting coefficient estimates with the marginal effects from equation 10. Since the linear probability model does not rely on the independence assumption for unbiasedness, this comparison provides a check for possible bias in marginal effects estimated from equation 10. As a second test, we vary the number of directions of spread L within each fire and test how results depend on how finely the spread directions are partitioned, since correlation among spread directions should decrease as the number of directions of spread within each fire is reduced. Finally, we include fire-specific fixed effects in our preferred specification of equation 9. Fixed effects account for a specific form of nonindependence in the probability of extinction across fires, namely, the existence of fixed differences in probabilities of extinction across fires. To ensure appropriate inference with respect to the marginal effects of suppression effort under violations of the independence assumption, we cluster standard errors by fire (Cameron and Miller, 2010).

5. Data

To estimate the model of fire spread distance, we use three primary categories of data: fire perimeters and ignition locations, determinants of suppression effort, and physical determinants of fire spread.

5.1 Wildfire data

Data describing areas burned come from the Monitoring Trends in Burn Severity (MTBS) project (MTBS, 2014). Since 1984, the MTBS project has used Landsat satellite imagery to map the geographic extent of all fires greater than 1,000 acres in size in the western United States. Therefore, estimated effects of suppression and variation in suppression effort across groups should be interpreted as representing suppression within the subset of fires that escape initial containment and grow to be relatively large. It is possible that suppression of these incidents differs from suppression of the broader set of wildfire ignitions, which would cause selection bias. For example, fires may fail to reach the 1,000-acre threshold for inclusion in the MTBS data set because they occur in especially dangerous areas and thus induce a more forceful response, or because they are weaker or more susceptible to suppression. The former is not a significant concern, since we account for variation in risk at each ignition point by using the spatial distribution of assets at risk as a proxy for effort. The latter has the potential to bias estimates of suppression effectiveness but would tend to bias the estimates toward zero.

Ignition locations are from the Fire Program Analysis fire-occurrence database (Short, 2017), which provides a comprehensive database of wildfires within the United States from 1993 to 2015 using a variety of federal, state, and local sources. Fires within the database include coordinates of each fire's point of origin accurate to within 1 km. The database includes even small ignitions that never grew to be threatening fires. In addition to restricting our attention to the set of fires that grew large enough to be mapped by MTBS, we focus on fires in the western United States in 1999–2015 whose ignitions were within 10 km of the wildland urban interface.[6] We focus specifically on the western United States because wildfire hazard is a significant concern in the region and because fire regimes in the western states are distinct from those in the east. The sample of fires is restricted to fires beginning within 10 km of the wildland urban interface for two reasons. First, due to concern over protection of private property, fires that begin within 10 km of the wildland urban interface are likely to induce the most forceful suppression responses. Indeed, some fires that begin in very remote areas are not suppressed and are instead managed to provide ecological benefits. Second, one of our interests is differences in suppression on behalf of varied communities. This set of fires includes only fires that directly threaten at least some human communities. Finally, we exclude from the sample all "complex" fires, large incidents in which multiple ignitions are jointly managed because of their close proximity to one another.

The remaining 1,503 fire ignitions, the locations of which are shown in Figure 1, constitute

[6]Wildland urban interface areas are those where developed residential areas intermingle with or are directly adjacent to large areas of wildland vegetation (US Department of Agriculture and Department of the Interior, 2001). Radeloff et al. (2005) mapped wildland urban interface across the U.S. at the US Census block level.

the full sample of fires analyzed in regression models that make use of US Census data to measure assets at risk. As described later, we also explore measuring assets at risk using assessors' data on housing locations and values.

To adapt the empirical model from the previous section to the data, we divide the area surrounding each wildfire ignition point into L directions of spread. Figure 2 provides an example. In the primary set of results, L equals 24 and each direction of spread has a central angle of 15 degrees, though we check for robustness of our results to varying values of L. We further divide each direction of spread into distance intervals of 1 km, up to a maximum distance (M) of 20 km, creating a circular grid surrounding each ignition location. We overlay the circular grid with the corresponding wildfire perimeter and code the fire as being extinguished ($y_{m\ell} = 1$) within a cell if the fire fails to reach a cell's centroid.[7] We code all prior cells (those nearer to the ignition point) within the direction of spread as burnt ($y_{m\ell}$ = 0). We refer to the distance interval at which the fire is first extinguished within each direction as interval M_ℓ, and we drop all observations within each direction ℓ for which $m > M_\ell$. Fires sometimes spread in irregular non-convex patterns, and they may return to a direction of spread from which they have previously been extinguished. We treat fires as remaining extinguished once they have first been extinguished within a direction of spread.[8] Figure 3 shows the distribution of fire spread distances. For almost 90% of spread directions, fires are extinguished within 5 km of the ignition point. Fewer than 0.5% of spread directions are right-censored by the maximum distance of 20 km, implying that estimates are unlikely to be biased due to omission of burnt areas beyond the maximum distance.

5.2 Determinants of fire suppression effort

Fire suppression effort is a function of at-risk assets within a given direction of spread, and of costs of suppression. To account for variation in suppression effort on behalf of populations at risk, we use a combination of US Census data, collected at the block and block group level, and parcel-level assessors' data. Census data describe the spatial distribution of households and population demographic characteristics, including income, a proxy for housing value. The primary advantage of Census data is that they are available across the full time span and spatial extent of the full sample of fires. A disadvantage is that variables are observed at relatively coarse spatial scales. While housing variables are available for the 2000 and 2010 Censuses at the block level, income and other demographic variables are available only at the Census block group level. To map Census block and block group data to the circular grids surrounding each ignition point, we

[7]Coding intervals as burnt if the fire burns any portion of the interval does not substantively change the results.

[8]An alternative would be to code $y_{m\ell}$ as 0 until the fire is finally extinguished within direction ℓ. Applying this alternative coding scheme does not substantively change the results.

assume that populations are uniformly distributed within each Census block and that Census blocks are demographically uniform within each block group. Given the large area of many Census block groups in rural parts of the western United States and the uneven nature of housing distributions across these large block groups, this approach may result in significant measurement error for income variables at the block group level.

To further investigate effects of housing values on suppression effort, we make use of parcel-level county assessors' data from CoreLogic, Inc. These data provide higher spatial resolution, as well as a direct measure of the value of structures threatened by each fire.[9] The primary disadvantage of these data, however, is that our data are limited to assessed values in 191 of 413 western counties from 2010 and 2011. Property values are likely to be influenced by the occurrence of a fire. To ensure that property value estimates are not affected by fires in the sample, we focus on fires occurring after 2011. Therefore, when using assessors' data, we limit the sample to the 179 fires indicated by red triangular markers in Figure 1.[10]

As is clear from Figure 2, the circular grid cells vary in area. The increase in affected area as fire spreads away from its point of origin captures a natural feature of spatial-dynamic phenomena: spread may be more damaging, and more costly to control, as it proceeds and the perimeter of the affected area expands (Epanchin-Niell and Wilen, 2012). Consistent with this feature of fire spread, we use area-dependent measures to capture both benefits and costs of controlling fire within a grid cell. Within models using Census data, we use the total number of housing units as a proxy for the number of homes in a cell. As a proxy for the total value of homes within each cell, we use the total number of housing units multiplied by per capita income, which we refer to as "total income."[11] To allow for the possibility that fire managers undertake greater suppression efforts on behalf of higher-income residents, we also include per capita income. While not central to our analysis, exploration of differences in suppression effort by race or other demographic characteristics would be of potential interest. However, because of a lack of variation in Census race variables, we focus on differences in effort by income and property value.[12]

For models using assessor data, we measure analogous variables for each grid cell: num-

[9] We measure structure value as the difference between the assessed property value and the assessed land value for each parcel.

[10] These fires are also included within the full sample, indicated by black circular markers.

[11] In theory, the number of housing units in an area could affect both the benefits and the costs of suppression, if suppression costs vary by housing density. We expect that differences in effects of density on fire spread will be captured by our fire simulation model outputs, described in the following subsection. Nevertheless, because our specification includes distance-from-ignition effects, which in our model control for the area of each circular grid cell, including the number of homes rather than the housing density has a minor effect on results.

[12] The assessors' data set contains no demographic data.

ber of residential properties, average value of residential properties, and total value of residential properties. More important than the value of residential properties within a cell is the value of structures, since land burned by a fire may still retain a significant portion of its value. While some counties collect assessed land values, which could be subtracted from assessed property values to yield a measure of structure value, assessments of land value are generally less accurate than property value assessments, and they are not collected by many counties. Therefore, in the assessor data models we use residential property values and consider them to be a proxy for residential structure values.

Benefit variables in the first panel of Table 1 summarizes demographic characteristics by distance from the ignition point; analogous variables based on assessors' data are summarized in the second panel. There is a clear trend in population density (as well as total income) over distance from the ignition point. This is likely due to selection: a fire is more likely to grow to be large, and therefore to be included in the sample, if it begins in a more rural location. This relationship suggests that, in estimating the effect of population on extinction probability, controlling for distance from ignition may be important to account for secular trends in demographic characteristics as well as to control for effects of duration dependence. Though protection of private property is a primary concern of fire managers, they may also be concerned with protecting a variety of other assets, including watersheds and threatened and endangered species habitat. We collected data describing the spatial distribution of these assets;[13] however, they did not have statistically significant effects on suppression effort, and so they are not included in the models presented here.

To account for differences in the cost of fire suppression over space, we collected data on accessibility and topographic ruggedness. We measured costs associated with ruggedness by calculating the topographic ruggedness index (TRI), which measures the variation in elevation among a pixel and its neighbors at a 30-m scale across the landscape surrounding each ignition point (Riley, 1999; Nunn and Puga, 2012). We then averaged TRI within each circular grid cell and multiplied average TRI by cell area to capture increases in costs due to expansion of the affected area. We measured accessibility as the total area within each cell that is within 0.5 km of a road. Another important factor affecting cost of effort is the availability of personnel and equipment resources. Firefighting resources shared across federal and state agencies are dispatched by a network of command centers according to need and availability (Bayham and Yoder, 2020). Some of the models estimated in the next section include fire-level fixed effects. National demand for and availability of firefighting resources varies over time but is likely relatively constant

[13] We collected data on the watershed significance of each circular grid cell (US Department of Agriculture, 2017), as well as the threatened and endangered species habitat within each cell (US Fish and Wildlife Service, 2017). For terrestrial threatened and endangered species, we measured the percentage of each cell classified as critical habitat, and for riparian species we measured the percentage of each cell that is within 0.5 km of threatened streams.

over the course of a wildfire incident. Therefore, fire-level fixed effects should account for differences across fires in availability of resources. The cost variables within Table 1 summarize how cost varies with distance from the ignition point. To better illustrate trends in distance from the ignition point, the table includes measures of these variables per area.

5.3 Physical fire spread variables

We control for natural factors affecting fire spread through inclusion of outputs from a model of fire spread. The US Forest Service has developed fire simulation software (including FARSITE, FlamMap, and FSPro), which differ in their applications to wildfire management. We use the Minimum Travel Time (MTT) model, which is the foundational fire simulation model underlying several of these programs, including FlamMap (used for landscape-scale wildfire risk assessment and planning) and FSPro (used during wildfire incidents to assess uncertainty and aid decisionmaking). Rather than explicitly predicting how a fire perimeter will expand across the landscape, MTT calculates the minimum travel time necessary for fire to travel among a two-dimensional network of nodes across the landscape. From these travel times, it interpolates fire arrival times. A key advantage of MTT is that it approximates more accurate models of fire behavior with relatively low computational cost (Finney, 2002), making it ideal for retrospective simulation of thousands of historical wildfires. MTT takes as inputs features of the landscape, such as elevation, slope, and aspect, and characteristics of vegetation on the landscape. As well, it requires the user to specify initial fuel conditions; fuel moisture then evolves over the course of the fire simulation. Topographic data and time-varying vegetation and fuel data come from the Landfire project (Landfire, 2014), which provides remotely sensed landscape data at a 30-m resolution.[14] Finally, MTT simulations take into account weather and wind values. We collected observed wind speed and wind direction at the time of each ignition from its nearest Remote Automated Weather Station (RAWS).[15]

Fire simulation models such as MTT perform well in predicting fire behavior and patterns of fire perimeter expansion across the landscape, but they are not designed to predict the final extent of a fire's spread—final fire perimeters from a fire simulation model are primarily a function of the length of time the simulation has been allowed to run. There-

[14] Vegetation characteristics include canopy cover, canopy height, canopy base height, canopy bulk density, and fuel models, which describe characteristics of fuels and how they respond to fire. Landfire collects vegetation characteristics from remote sensing data with a resolution of 30 m. Since 2008, Landfire vegetation data have been updated every two years, but Landfire was not updated between 2000 and 2008. We use 2000 Landfire data for 2000–2005, 2008 data for 2006–2010, and 2010, 2012, and 2014 data for the two years following each of those updates.

[15] The RAWS system is a network of automated weather stations, including many in remote locations, maintained by federal land management agencies to monitor fire danger and air quality and to provide weather data for research purposes.

fore, rather than limit the duration of each simulated fire, we allowed each simulated fire to burn until it entirely consumed the landscape within 20 km of its ignition point. Forcing the 20-km circular grid to be entirely consumed by fire generates a series of landscape-wide measures describing how fire would be expected to burn within a 30-m pixel, conditional on fire having reached that pixel. Among these measures are landscape-wide surfaces of fire intensity and fire arrival time. Fire intensity measures heat generation per unit time within a pixel, while fire arrival time measures the time since fire ignition at which a fire is expected to reach a given 30-m pixel. We measure arrival time within circular grid cell $m\ell$, which we denote $T_{m\ell}$, as the time at which fire is expected to reach the centroid of the cell. Previous studies have used the rate of fire spread as a predictor for fire extinction (Peterson et al., 2009), and it is reasonable to expect that fire will be more likely to stop spreading where it travels more slowly. Therefore, we calculate $\Delta T_{m\ell} = T_{m\ell} - T_{m-1,\ell}$,[16] and we use this discretized rate of spread between cells as our primarily predictor of the effects of physical factors on the probability of fire extinction.[17] We simulated fire spread for each of the 1,503 wildfires in the sample. An example of how MTT outputs are used is provided in Figure 4. Panel A illustrates the surface of simulated arrival times across the landscape surrounding an example fire ignition. Panel B illustrates the outcome of averaging arrival times within cells and taking differences across successive cells.

MTT does not simulate fire spread within areas without fuel (e.g., highly urbanized areas or water bodies). Therefore, we code the average arrival time of a fire within a circular grid cell as missing if fuel is absent for more than 50% of pixels within a cell. Fire rate of spread may affect fire extinction in a nonlinear way, and fire is more likely to stop spreading when it reaches areas without fuel. In the spread-distance model described by equation 10, we account for effects of rate of spread on extinction using $\ln(\Delta T + 1)$ as well as a variable indicating whether the majority of 30-m pixels within a cell lack fuel (ΔT missing). We account for wildfire intensity using $\ln(Intensity + 1)$. Further, we supplement MTT outputs with an indicator variable describing whether a primary or secondary road crosses each cell, since roads provide a major barrier to fire spread that is not fully captured by MTT. Altogether, we specify the effects of physical factors on extinction probability through the function

$$g(\mathbf{z}_{m\ell}) = \gamma_1 \ln \Delta(T_{m\ell} + 1) + \gamma_2 \ln(Intensity_{m\ell} + 1) + \gamma_3 1(No\ fuels) + \gamma_4 MajorRoad_{m\ell}, \tag{11}$$

where $\ln(\Delta T_{m\ell} + 1)$, and $\ln(Intensity_{m\ell} + 1)$ is coded as 0 if fuel is absent in cell $m\ell$. Table 1 describes how $Intensity$, T, ΔT, and the fraction of cells without fuel vary with distance from the fire ignition point. As one would expect, arrival time T increases with distance from the ignition point. Rate of spread decreases with distance from the

[16]For cells such that $m = 1$, $\Delta T = T_{m\ell}$.

[17]In some cases, fire spreads in irregular patterns such that $\Delta T < 0$. In these cases, ΔT is coded as missing.

ignition point, whereas the number of cells in which fuel is absent increases with distance, suggesting that areas farther from a fire's site of origin are less likely to be favorable for fire growth.

6. Results

Because the assessor data most accurately measure structures at risk, we begin with an analysis using these data. Table 2 provides results based on estimates of the fire spread model using these data and the 2012–2015 limited sample. Each model in the table includes distance-from-ignition fixed effects and include variables only at the fire's current point of spread. That is, we exclude spatial leads and restrict ν_0 and $\bar{\nu}$ within equation 10 to equal 0. In columns 1–4, we assume that extinction probability can be represented by an exponential proportional hazard, which implies that equation 7 can be estimated using a standard complementary log-log likelihood function. For these columns, we report marginal effects calculated at variable means. Column 1 of the table includes only suppression-effort variables. Results suggest that fires are more likely to stop spreading in cells containing a greater number of residential properties, especially when the average value of those properties is greater. The marginal effect of average property value indicates that each \$100,000 increase in the average property value increases the probability of extinction within the cell by nearly 3 percentage points, compared with a baseline probability of 38%. Fires are also more likely to stop spreading in less rugged and more accessible cells.

Column 2 reports marginal effects from a complementary log-log regression that includes only fire spread variables. Each variable is related to fire extinction probability with a high degree of statistical significance. As fire speed slows, the probability that the fire will go out increases; for every 10% increase in $\Delta T + 1$, the probability of extinction increases by 1.3 percentage points. The probability of extinction also increases when the fire encounters a cell containing a major road or a cell where fuel is absent. When fire encounters a cell where US Geological Survey Landfire data record that more than 50% of the cell area contains no fuel, the probability that the fire stops spreading increases by 51 percentage points. Finally, fires are more likely to stop spreading in cells where they burn more intensely. While this result may seem counterintuitive, it may have to do with the fact that fires frequently stop their spread along ridgelines, where fire intensity also peaks.

As discussed previously, identification of the effects of fire suppression using assets at risk as a proxy for suppression effort requires accounting for the effects of physical factors and fuels because fuels are likely to be spatially correlated with assets at risk. Column 3 includes both effort and fire spread variables. The corresponding coefficients generally diminish in magnitude when included within the same regression. This suggests that, as expected, failing to account for effects of physical factors on fire spread biases estimates of the effects of suppression effort away from zero. In column 4, fire fixed effects are added to the regression. Fire fixed effects account for fixed differences in extinction probability across fires, possibly due to differences in fuel moisture or fire weather across incidents or availability of resources. Coefficient estimates for housing variables generally increase in magnitude with the inclusion of fire fixed effects. This suggests that fires that begin near more populated areas are less likely to spread, perhaps due to additional suppression effort applied regardless of spread direction.

To test the assumption regarding the form of the fire extinction probability function (equation 8) and the assumption of independence between fire spread directions, columns 5, 6, and 7 provide marginal effects for estimates of equation 10 using logit regressions, probit regressions, and coefficient estimates from a linear probability model, respectively. Estimates and standard errors are similar across specifications, indicating that the results are not sensitive to the assumptions used to develop the model.

Table 3 presents parallel results to Table 2 using Census data and the full set of 1,503 wildfires. With Census data, we sacrifice some accuracy in our measures of housing and property values for a substantially increased sample size. Census data allow us to make use of fires across all western US counties dating back to 1999. Results based on Census data are qualitatively similar to results based on assessor data. Fires are more likely to stop spreading within cells that contain greater numbers of homes, especially if per capita income within the cell is greater. Table 3 indicates that an increase in per capita income of $10,000 is associated with a 1 percentage point increase in the probability that the fire stops spreading within the cell.

In contrast to the marginal effect of property value reported in Table 2, the estimated effect of per capita income is small. An average household could afford an approximately $100,000 larger mortgage with $10,000 additional income per person per year.[18] Yet, compared with the estimated 1 percentage point effect of a $10,000 increase in per capita income (Table 3), Table 2 indicates that the probability of extinction increases by more than 2 percentage points when property value rises by $100,000 per year. The attenuated estimate with the Census data is likely driven by error in measuring per capita income at the Census block group level. Household units within each cell are measured using Census blocks, and estimates are quite similar to those obtained with assessor data, though they are measured more precisely.

As in Table 2, columns 5–7 indicate that the results are not sensitive to the choice of extinction probability functional form or to the assumption of independence among fire

[18] This assumes a 30-year mortgage with an interest rate of 4% and that the household contains 2.6 people (the national average) and spends 25% of its income on housing.

spread directions. To provide a further test of independence among fire spread directions, Table 4 shows results from regressions specified as in column 4 of Tables 2 and 3, but estimated using data constructed with alternative numbers of fire spread directions around each ignition point. From column 1 to 3 and from column 4 to 6, fire spread directions become more expansive, and the number of observations per fire declines. Nonetheless, the results are broadly similar across the columns. As would be expected, estimates attenuate and standard errors increase as the number of fire spread directions declines, but even in columns with just six directions of spread, some coefficients are statistically significant. These results suggest that the assumption of independent discrete directions of spread is not driving results.

For simplicity, the specifications presented thus far have assumed that only characteristics of a fire's present location affect its spread. As discussed in the theory section, however, fire managers may be spatially forward-looking and seek to prevent fire spread toward particularly valued areas. In Figure 5, we present results from models that set $\bar{\nu} = 5$ and therefore include "spatial leads" that account for anticipatory behavior among fire managers. Spatial leads included within the effort function are highly correlated with one another; a cell that contains many homes is likely to be near other cells with many homes. Therefore, as is typical of distributed lag models, estimates of lead effects are imprecise and unreliable. To improve estimates of spatial leads we smooth estimates using a restricted distributed lead model. Specifically, following Almon (1965), we assume that spatial lag weights follow a polynomial function, where each spatial lead coefficient is defined as $\beta^{\nu} = \sum_{\tau=0}^{\bar{\tau}} a_{\tau} \nu^{\tau}$.[19] The advantages of restricted distributed lag (in this case, distributed lead) models are that they reduce the number of parameters to be estimated and ensure that weights follow a smooth function of ν. Their primary disadvantage is that, in doing so, they impose assumptions regarding the form of the model. Therefore, we also present results from models estimated using unrestricted spatial leads.

Figures 5a and 5b illustrate distributed lead weights from models based on, respectively, assessor data and the limited 2012–2015 fire sample, and Census data and the full sample of fires. The Almon weighting specification assumes that spatial weights follow a quadratic function. Both specifications assume weights fall to zero by 6 km from the fire's current location. Coefficient estimates for each model are presented in the appendix in Tables A1–A4. As expected, weights generally decline with distance from the focal cell, falling to zero at a distance of approximately 3 km. Results are fairly similar across specifications using unrestricted and Almon weights, though the tendency for weights to "bounce" up and down is reduced by the use of Almon weights. Similarly to

[19] We modify the Almon weighting scheme slightly for effort variables representing factors correlated with costs (e.g., percentage of cell accessible by road). Upon a fire's reaching a cell, high costs may decrease the probability that the fire is extinguished there. However, if managers anticipate higher costs were the fire to spread farther, they may be induced to allocate additional effort at the fire's current point of spread. To account for the possibility that cost variables have different effects within the reference cell than within lead cells, we relax the restrictions of the Almon and linear weighting schemes for reference cell cost coefficients.

previous results, fires are more likely to stop spreading as they approach cells with residential properties, cells with more homes, and cells where those homes are worth more (or where per capita income is greater). A possible concern with the results presented in Tables 2 and 3 is that fire simulation variables do not adequately control for the effects of fuel on fire spread, and so results reflect the direct effect of homes on fire spread via fuel rather than effects due to increased suppression effort. Results in Figure 5 provide evidence of spatially forward-looking behavior in fire management and provide confidence that suppression effort on behalf of homes is driving the results; residential properties 2–3 km away from a fire's current location can affect fire spread through suppression effort, but not through fuel.

To aid in interpreting these results and to facilitate comparisons among the magnitudes of housing coefficients, Table 5 presents predicted changes in the probability of extinction based on changes in housing 1 km from the focal cell. Estimates are based on the assessor data model with quadratic Almon weights. Scenario I shows the difference in probability of extinction when the cell 1 km beyond a fire's current extent of spread increases from zero residential properties to the mean number and value of residential properties among all populated cells. Specifically, when the number of residential properties 1 km away increases from zero to 10, each with an average value of $200,000, the probability of extinction increases by 5.9 percentage points above a baseline probability of 38%. In Scenario II, the initial number and value of properties is set at 10 and $200,000, and we test the effects of a number of changes to housing within the cell. First, we increase the average value of properties within the cell while holding the number of residential properties constant. Next, we increase the number of properties while holding the average value of properties constant. Finally, we increase the average value of properties, while holding the total value of properties constant, which requires also decreasing the number of properties within the cell. These experiments reveal that the weight given to property value is quite high. Doubling the number of properties while holding the average value constant produces only a 0.1 percentage point increase in the probability of extinction. Yet doubling the average value of properties, which yields an equivalent increase in total housing value, increases the probability of extinction by almost 3 percentage points. Even when the number of properties decreases, increasing the average value of properties within a cell yields an increase in the probability of extinction (Scenario IIC). In Scenario III, the initial number and value of homes are set to higher values. Here, increasing the number of homes within the cell by 10 homes no longer yields a statistically significant increase in the probability of extinction. However, increasing the average value of homes produces a statistically significant 2–3 percentage point increase in the probability of extinction, depending on whether the total housing value is held constant. The difference between the results in Scenarios IIIA and IIIC is driven by the negative effect of total value on the probability of extinction (see Figure 5a), which suggests a diminishing effect of property value on the probability of extinction as the number of residential properties increases.

7. Discussion

Federal expenditures on fire suppression reached $3.14 billion in 2018, a fourfold real increase compared with 1985–1989 (National Interagency Fire Center, 2020). Despite the increase in expenditures, over 10 million acres burned in 2018, compared with an average of 3 million acres during the late 1980s. Westerling et al. (2006) find that in the western United States, increases in the frequency of large wildfires after the mid-1980s are strongly associated with changes in climatic factors, suggesting that continued increases in the scale and cost of western wildfires are likely. Climate-driven increases in wildfire activity are also anticipated for other regions of the world (Shukla et al., 2019).

This paper uses a novel empirical approach to evaluate the effectiveness of wildfire suppression and examine the factors that determine the allocation of fire suppression resources in large fires. Our approach compares historical wildfire perimeters to the spatial distribution of assets at risk on the landscape to understand how fire suppression was applied in defense of those assets. To account for differences in fire spread due to physical factors like topography, vegetation, and wind, we use a fire simulation model to simulate fire spread in the absence of suppression for each fire in our data set; we use outputs from these fire simulations as controls within our empirical model. Our estimates provide insight into what drives the allocation of suppression resources and how effective these resources are in protecting assets at risk. Further, this new approach for evaluating fire management responses reflects the spatial and dynamic complexities of wildfire management. Rather than simply considering the effects of resources at risk and landscape characteristics within a neighborhood of the ignition point on management outcomes, our approach accounts for the complete spatial profile of landscape features, allowing us to test whether fire managers allocate suppression resources in a forward-looking manner.

Our estimates indicate that fire suppression is shaped by both built and natural landscape features. While the baseline probability of suppression at a given point along an average fire's path through undeveloped terrain is roughly 38%, we find that fire spread is 16% more likely to be halted when a fire is approaching a typical (in terms of number and value of properties) inhabited area. When the average value of properties in the fire's path increases from $200,000 (average) to $400,000, the probability of suppression increases by another 6.2%. Taken together, these two estimates imply that differential suppression activity based on the priorities of fire managers can increase the probability of extinction at a given point in a fire's path by more than 20%. Moreover, we find evidence that both natural and built landscape features affect extinction probabilities even when they are located some distance from the fire's front. The presence of houses, the number of houses, and the average value of houses at a distance of 2–3 km all increase the likelihood that a fire will be halted.

To simplify our spatial-dynamic analysis, we assume fires spread linearly from their ignition points. While we believe this simplification is justified, it may lead us to incorrectly measure the anticipated directions of fire spread, thus attenuating our estimates of the effect of suppression activity on fire spread. Nevertheless, our findings provide evidence that fire suppression can substantially influence the spread of large wildfires, a hypothesis for which there has thus far been surprisingly little evidence. Furthermore, the findings provide evidence that some households and communities may benefit disproportionately from fire suppression.

There are several explanations for our finding that higher-value homes benefit disproportionately from fire suppression. First, setting aside obvious concerns of fairness and equity, a policy of more aggressively defending higher-value properties would be optimal from the perspective of minimizing damages. However, a policy of simply minimizing losses is inconsistent with the results in Table 5, which show that conditional on total value, there are differential effects from increasing the number of homes and increasing the value of homes. Furthermore, we think it is unlikely that management decisions would so explicitly favor higher-value properties. Nevertheless, fire management decisionmaking may favor wealthier communities because of concerns among fire managers over political repercussions if such communities were to lose homes in a fire.

While we are interested in how fire management affects outcomes for homes, we choose to focus in this paper on fire spread rather than property loss. Fire perimeters represent the outer extent of a fire's spread, and fire intensity and impacts can vary substantially inside the perimeter. Not all structures within a fire perimeter are necessarily destroyed or even damaged. Moreover, properties outside a fire's perimeter can sometimes incur damage due to the spread of embers, which can travel up to 2 km from a fire's periphery (Keeley and Syphard, 2019). Nevertheless, it is reasonable to expect that properties inside a fire's perimeter are substantially more likely to incur damage, and focusing on fire spread rather than structure loss buttresses our identification strategy.

The identifying assumption underlying our strategy is that, after controlling for fire simulation outputs, there are not unobserved factors correlated with both fire suppression effort and resources at risk. Were we to focus on home destruction rather than on fire spread, we might worry about unobserved factors such as firefighting services available only to owners of high-priced insurance policies, or private risk mitigation activities undertaken disproportionately by owners of expensive properties. While such activities might affect rates of property loss, we believe they are unlikely to affect the extent to which a fire spreads.[20] Further supporting the idea that fire suppression drives the observed correlation between resources at risk and fire spread is our finding that fire extinction is correlated with characteristics of properties 2–3 km outside a fire's current

[20]Unlike public land management agencies, who are focused on controlling fire spread—for example by building containment lines—private firefighting services are typically focused on defending structures.

perimeter, likely reflecting anticipatory behavior on the part of fire managers.

In addition to the literature on wildfire management, this paper contributes to the literature on spatial-dynamic resource management. A distinguishing characteristic of our spatial duration model is that it relies on the fact that fires, once extinguished, stop their spread permanently. This feature is not shared by some other spatial-dynamic resource management problems, such as biological invasions, which can sometimes reinvade areas from which they have been previously exterminated. While the spatial duration model we apply in this paper could not be directly applied to such problems, related methods could be developed that take advantage of more detailed temporal data on invasion spread. Thus, this paper provides an example of how empirical methods can be adapted to examine complex spatial-dynamic management problems, which economists have mostly considered only in normative theoretical papers.

Finally, this paper contributes to the literatures on environmental justice and adaptation to climate change. Government will likely play a substantial role in climate adaptation, perhaps especially in response to climate-driven disasters. This paper suggests that responses to these events may shape outcomes in inequitable ways.

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Figure 1. Geographic distribution of fires within the sample. The sample includes 1,503 fires that occurred in 1999–2015, were large enough to be mapped by the Monitoring Trends in Burn Severity project, and began within 10 km of a wildland urban interface area. Complex fires are excluded.

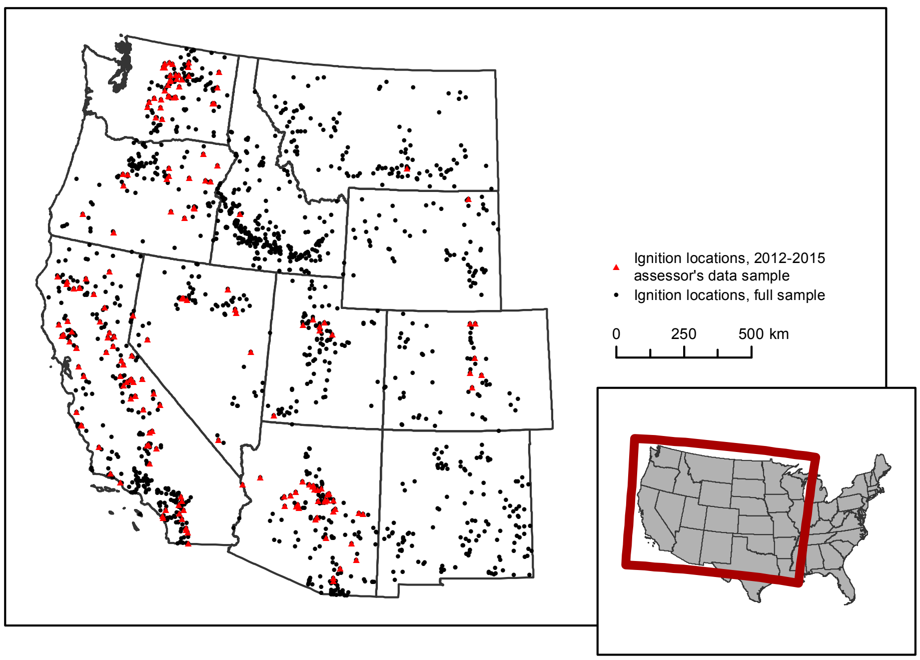


Figure 2. Illustration describing the construction of the data set. The landscape surrounding each ignition point is divided into 24 discrete directions of spread. Each direction of spread is divided into 1-km distance intervals, up to a maximum distance of 20 km, yielding a circular grid surrounding each ignition point in the data set. Cells are coded as burnt if fire reaches the cell centroid.

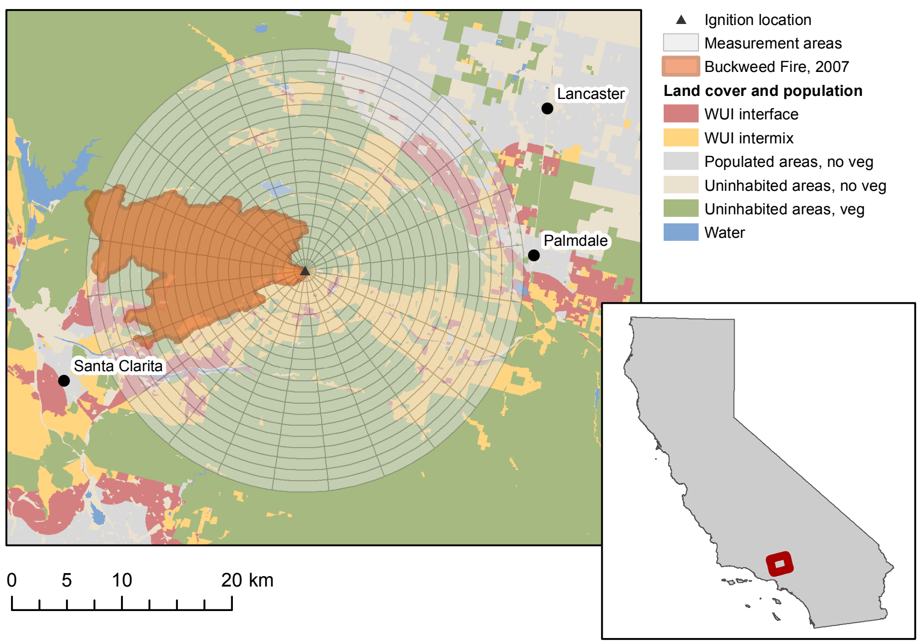


Figure 3. Histogram of fire spread distances. The figure shows the distribution of fire duration for 1,632 fires and 20,663 directions of spread. Fires are extinguished within 5 km of the ignition point for nearly 90% of spread directions. Fires burn beyond the maximum observed distance of 20 kilometers in fewer than 0.5% of spread directions.

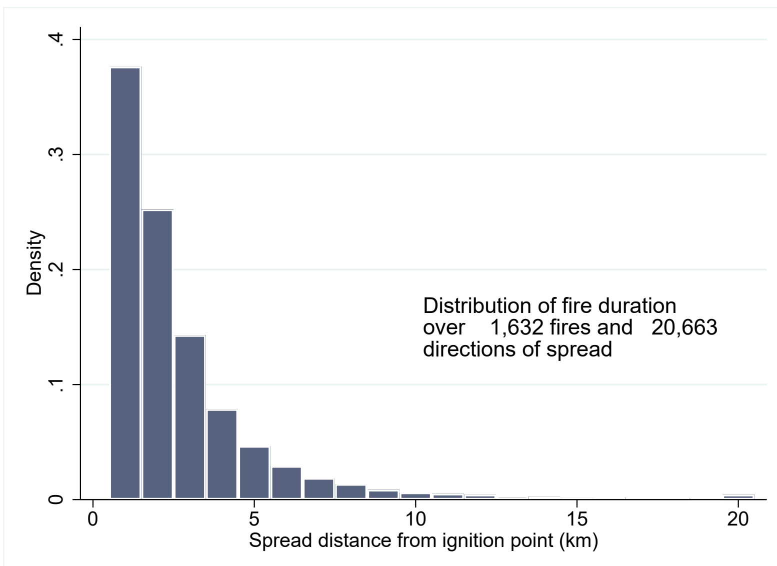


Figure 4. Illustration of fire simulation output.

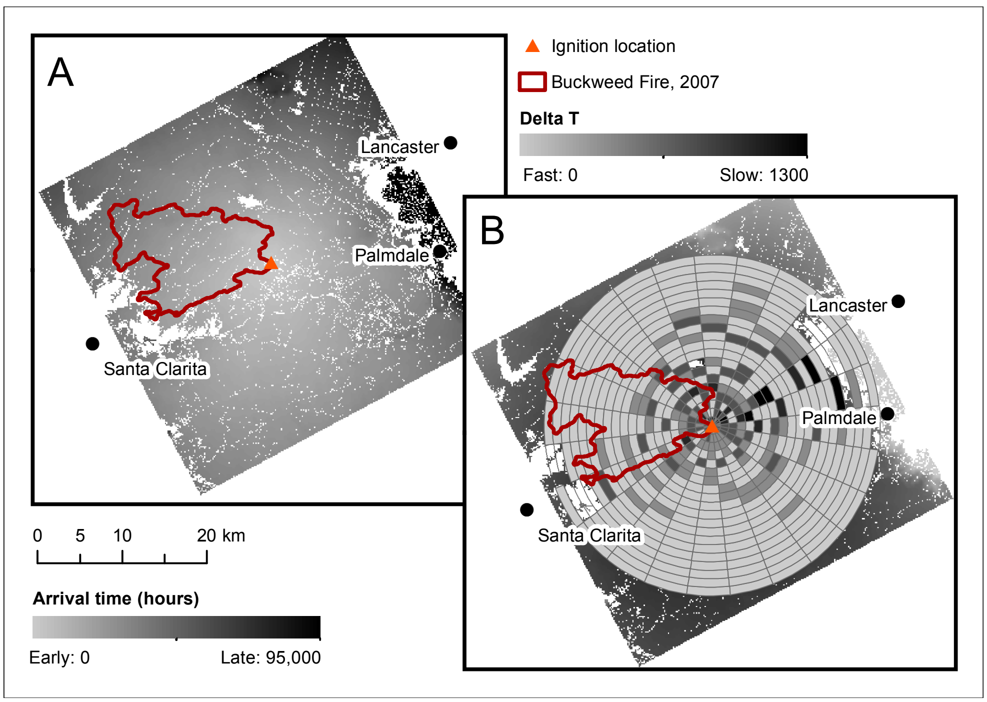
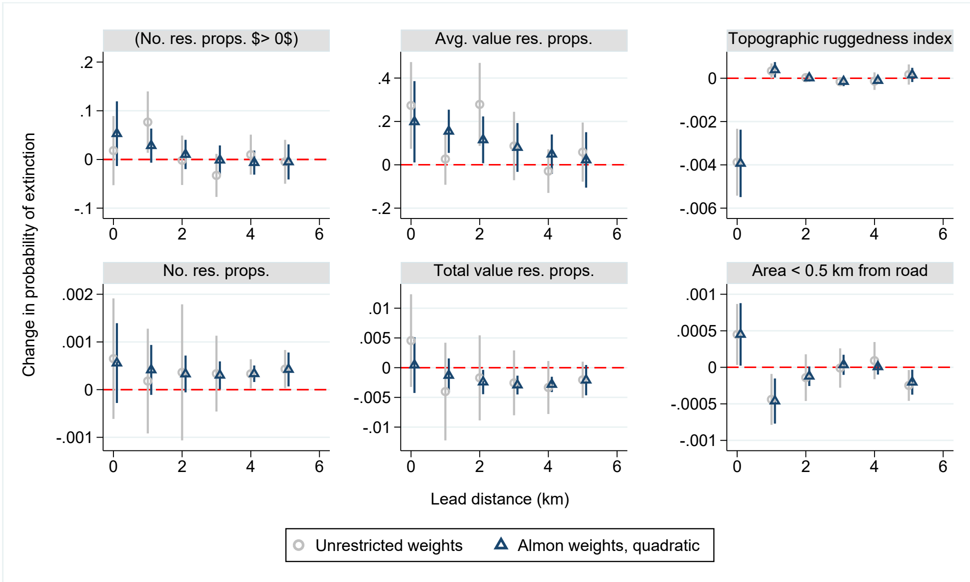
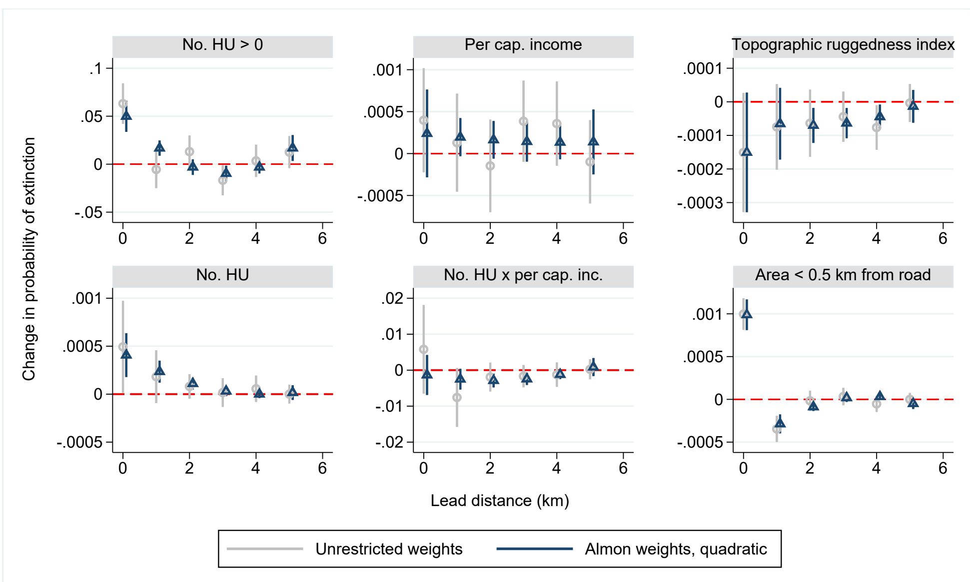


Figure 5. Weights estimated from distributed spatial lead models using housing variables from Census data and California assessors' data.



(a) Assessors' data



(b) Census data

Table 1. Summary statistics for circular grid cell-level observations, by distance from fire ignition point

	(1) 0–5 km	(2) 5–10 km	(3) 10–15 km	(4) 15–20 km	(5) Whole Sample
I. Full sample					
Benefit variables					
No. of housing units > 0	.545	.619	.658	.685	.627
No. of housing units	4.9	21.8	41	65.4	33.1
Housing unit density (housing units/sq. km)	6.23	11	12.5	14.2	11
Per capita income (thousands USD)	29.1	29.1	29.1	29.2	29.1
Total income (millions USD)	.172	.727	1.4	2.18	1.11
Cost variables					
Avg. topographic ruggedness index	19.4	17.5	17.3	16.6	17.7
Pct. within 0.5 km of roads	59.8	59.8	59.2	58.5	59.3
Fire spread variables					
T (hours since ignition)	52.4	124	193	208	142
ΔT (hours until arrival in next cell)	16.4	14.2	14.1	14.1	14.8
(No fuel)	.157	.223	.249	.413	.26
Fire intensity (kW/hour)	281	307	303	298	297
Contains major road	.0723	.112	.152	.187	.13
No. of obs.	179,195	177,895	176,667	175,412	709,169
II. 2011–2015 Assessors' Data Sample					
No. of residential properties > 0	.111	.173	.211	.241	.184
No. of residential properties	4.5	22.1	39.4	54.3	30
No. of residential properties/sq. km	6.14	10.9	12.1	11.9	10.2
Avg. residential property value (millions USD)	.292	.288	.307	.305	.299
Total value of residential properties (millions USD)	1.48	5	8.95	13.5	7.22
No. of obs.	45,994	45,822	45,721	45,623	183,160

Table 2. Results from regressions using assessors' data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(No. of res. props. > 0)	.071		.0051	.045	.054	.058	.049
	[.043]		[.031]	[.039]	[.041]	[.039]	[.036]
No. of res. props.	.0014		.00092	.0012	.0011	.0012	.0014
	[.00051]		[.00069]	[.00046]	[.00066]	[.00064]	[.00063]
Avg. value of res. props. (millions USD)	.23		.28	.26	.27	.27	.31
	[.11]		[.092]	[.1]	[.11]	[.11]	[.098]
Total value of res. props. (millions USD)	-.0041		-.001	-.0039	-.0032	-.0037	-.0046
	[.0038]		[.0034]	[.0027]	[.0042]	[.0036]	[.0032]
Topographic ruggedness index	-.0041		-.0082	-.0052	-.0046	-.004	-.0031
	[.001]		[.001]	[.00097]	[.00087]	[.00075]	[.00069]
Pct. < 0.5 km from road	.00056		-.000018	.00024	.0002	.00016	.00011
	[.00025]		[.00024]	[.00024]	[.00022]	[.00021]	[.00016]
Ln($\Delta T + 1$)		.1	.045	.1	.092	.09	.091
		[.017]	[.014]	[.017]	[.016]	[.016]	[.016]
Ln(Intensity)		.096	.058	.1	.095	.092	.095
		[.02]	[.012]	[.02]	[.018]	[.018]	[.019]
Contains major road		.19	.19	.18	.19	.19	.19
		[.032]	[.031]	[.032]	[.036]	[.035]	[.037]
ΔT missing		.37	.22	.36	.36	.35	.35
		[.046]	[.039]	[.046]	[.046]	[.045]	[.047]
Specification	Comp. log-log	Comp. log-log	Comp. log-log	Comp. log-log	Logit	Probit	LPM
Fire fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
No. of obs.	11,096	11,096	11,096	11,096	11,096	11,096	11,096
No. of fires	179	179	179	179	179	179	179

Note: Spatial leads are omitted. Marginal effects are reported for complementary log-log, logit, and probit specifications; coefficient estimates are reported for ordinary least squares. All models include distance from ignition fixed effects. Standard errors are in parentheses and are clustered by fire.

Table 3. Results from regressions using Census data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(No. of HU > 0)	.079		.025	.065	.065	.065	.065
	[.012]		[.0099]	[.011]	[.01]	[.01]	[.0097]
No. of HU	.00096		.00071	.00078	.0013	.001	.00059
	[.00036]		[.0002]	[.00037]	[.00044]	[.00039]	[.00024]
Per capita income	.0012		.00076	.00074	.00062	.00061	.00059
	[.00037]		[.00029]	[.00033]	[.00033]	[.00033]	[.00029]
No. of HU $\times$ per capita income	-.0062		-.0067	-.0048	-.0085	-.0073	-.0015
	[.0075]		[.0046]	[.0076]	[.0078]	[.0073]	[.005]
Topographic ruggedness index	-.000016		-.00096	-.00012	-.00012	-.00011	-.000053
	[.000069]		[.00068]	[.00011]	[.0001]	[.000076]	[.000036]
Pct. < 0.5 km from road	.0012		.0011	.00094	.00086	.0008	.00067
	[.0001]		[.00012]	[.000093]	[.000087]	[.000083]	[.000074]
Ln($\Delta T + 1$)		.13	.079	.13	.12	.12	.12
		[.0063]	[.0057]	[.0062]	[.0062]	[.006]	[.0061]
Ln(Intensity)		.11	.06	.11	.1	.1	.11
		[.0075]	[.0045]	[.0075]	[.007]	[.0065]	[.0069]
Contains major road		.18	.14	.14	.16	.16	.16
		[.013]	[.013]	[.013]	[.015]	[.014]	[.015]
ΔT missing		.5	.35	.48	.49	.49	.5
		[.016]	[.016]	[.016]	[.017]	[.016]	[.018]
Specification	Comp. log-log	Comp. log-log	Comp. log-log	Comp. log-log	Logit	Probit	LPM
Fire fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
No. of obs.	88,568	88,568	88,568	88,568	88,568	88,568	88,568
No. of fires	1,503	1,503	1,503	1,503	1,503	1,503	1,503

Note: Spatial leads are omitted. Marginal effects are reported for complementary log-log, logit, and probit specifications; coefficient estimates are reported for ordinary least squares. All models include distance from ignition fixed effects. Standard errors are in parentheses and are clustered by fire. HU refers to housing units.

Table 4. Results from regressions with varying numbers of directions of spread in each fire, using Census variables

	Assessors' Data			Census Data		
	(1)	(2)	(3)	(4)	(5)	(6)
(No. of res. props. > 0)	.053	.066	.049			
	[.043]	[.039]	[.049]			
No. of res. props.	-.00059	.00018	.000073			
	[.00054]	[.00016]	[.00012]			
Avg. value of res. props. (millions USD)	.25	-.017	.087			
	[.095]	[.076]	[.2]			
Total value of res. props. (millions USD)	.0013	-.0014	.0045			
	[.0028]	[.00093]	[.0033]			
(No. of HU > 0)				.071	.059	.068
				[.011]	[.013]	[.014]
No. of HU				.0013	.00072	.00014
				[.00069]	[.00023]	[.000088]
Per capita income				.00083	.00062	.00047
				[.00034]	[.00036]	[.00036]
No. of HU $\times$ per capita income				-.009	-.0084	.00071
				[.014]	[.0054]	[.0022]
Topographic ruggedness index	-.0083	-.0033	-.00094	-.00024	-.00017	-.00011
	[.0019]	[.00062]	[.00049]	[.00018]	[.00012]	[.000068]
Pct. < 0.5 km from road	.0016	.00039	.0002	.0018	.00058	.00024
	[.0004]	[.00017]	[.00014]	[.00016]	[.000067]	[.00005]
Ln($\Delta T + 1$)	.09	.084	.12	.11	.13	.14
	[.016]	[.02]	[.024]	[.006]	[.0067]	[.0083]
Ln(Intensity)	.058	.12	.16	.068	.15	.18
	[.015]	[.023]	[.032]	[.0059]	[.0089]	[.011]
Contains major road	.17	.14	.12	.15	.12	.11
	[.035]	[.035]	[.038]	[.014]	[.014]	[.016]
ΔT missing	.33	.35	.42	.41	.48	.53
	[.046]	[.058]	[.077]	[.016]	[.019]	[.024]
Directions of spread	48	12	6	48	12	6
Fire fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	20,831	5,382	2,558	166,822	41,393	20,589
No. of fires	170	171	162	1,451	1,394	1,338

Note: Spatial leads are omitted. Standard errors are in parentheses and are clustered by fire. HU refers to housing units.

Table 5. Estimated changes in probability of extinction due to changes in cell housing stocks from three different baselines 1 km from the focal cell; calculated from a linear probability model with five spatial leads, restricted using quadratic Almon weights

	No. of res. props.	Avg. value of res. props. (millions USD)	Tot. val. of res. props. (millions USD)	$\Delta Pr(y=1)$	SE
Scenario I: Initial values	**0**	**0**	**0**		
A. Increase variables to mean within populated cells	10	.2	2	.059	(.013)
Scenario II: Initial values	**10**	**.2**	**2**		
A. Increase avg. value while holding no. of properties constant	10	.4	4	.027	(.0093)
B. Increase no. of properties while holding avg. value constant	20	.2	4	.0011	(.00063)
C. Increase avg. value while holding total value constant	5	.4	2	.028	(.0092)
Scenario III: Initial values	**20**	**.3**	**6**		
A. Increase avg. value while holding no. of properties constant	20	.5	10	.023	(.01)
B. Increase no. of properties while holding avg. value constant	30	.3	9	-.00063	(.0018)
C. Increase avg. value while holding total value constant	12	.5	6	.026	(.0092)

Note: Initial values in Scenario II reflect approximate average value and number of properties within populated cells. More precisely, the average value of properties is $170,000 and the average number of properties is 9.75.

Table A1. Results from linear probability model estimated with 5 unrestricted distributed spatial leads for variables related to benefits and costs of fire suppression. Housing variables are drawn from county assessors' data

	Spatial leads					
Variable	m	$m+1$	$m+2$	$m+3$	$m+4$	$m+5$
(No. res. props. > 0)	.018	.077	-.0017	-.033	.0099	-.0048
	(.036)	(.032)	(.026)	(.022)	(.021)	(.023)
No. res. props.	.00065	.00018	.00036	.00034	.00033	.00043
	(.00064)	(.00056)	(.00072)	(.0004)	(.00015)	(.0002)
Avg. value res. props. (millions USD)	.27	.027	.28	.087	-.029	.059
	(.1)	(.06)	(.097)	(.08)	(.051)	(.069)
Total value res. props. (millions USD)	.0046	-.004	-.0017	-.0026	-.0033	-.002
	(.0039)	(.0042)	(.0036)	(.0028)	(.0023)	(.0015)
Topographic ruggedness index	-.0039	.00034	.000029	-.00016	-.00013	.00017
	(.00078)	(.00018)	(.000086)	(.000097)	(.00021)	(.00024)
Pct. < 0.5 km from road	.00045	-.00044	-.00014	-9.4e-06	.000092	-.00025
	(.00021)	(.00018)	(.00016)	(.00014)	(.00013)	(.00011)
Ln(ΔT 1)	.095					
	(.016)					
Ln(Intensity)	.097					
	(.019)					
Contains major road	.2					
	(.038)					
ΔT missing	.36					
	(.049)					
Fire fixed effects	Yes					
Number obs.	10861					
Number fires	178					

Note: All models include distance from ignition fixed effects. Standard errors are in parentheses and are clustered by fire. HU refers to housing units.

Table A2. Results from linear probability model estimated with five unrestricted distributed spatial leads for variables related to benefits and costs of fire suppression, with proxies for housing from US Census data

	Spatial leads					
Variable	m	$m+1$	$m+2$	$m+3$	$m+4$	$m+5$
(No. of HU > 0)	.063	-.0055	.013	-.017	.0035	.013
	(.011)	(.0099)	(.0086)	(.008)	(.0086)	(.0085)
No. of HU	.00049	.00018	.00008	.000017	.000056	4.5e-07
	(.00024)	(.00014)	(.000065)	(.000076)	(.00007)	(.00005)
Per capita income (thousands USD)	.0004	.00013	-.00015	.00039	.00036	-.000098
	(.00032)	(.0003)	(.00028)	(.00025)	(.00026)	(.00025)
No. of HU $\times$ per capita income	.0058	-.0076	-.0019	-.0017	-.0012	.00024
	(.0063)	(.0042)	(.002)	(.0016)	(.0017)	(.0014)
Topographic ruggedness index	-.00015	-.000075	-.000064	-.000044	-.000076	-3.5e-06
	(.00009)	(.000065)	(.000051)	(.000038)	(.000034)	(.000029)
Pct. < 0.5 km from road	.001	-.00035	-.000017	.000033	-.000053	-1.3e-07
	(.000094)	(.000078)	(.000061)	(.000052)	(.000048)	(.000038)
Ln(ΔT 1)	.12					
	(.0062)					
Ln(Intensity)	.11					
	(.0069)					
Contains major road	.16					
	(.015)					
ΔT missing	.51					
	(.018)					
Fire fixed effects	Yes					
No. of obs.	86,948					
No. of fires	1,499					

Note: All models include distance from ignition fixed effects. Standard errors are in parentheses and are clustered by fire. HU refers to housing units.

Table A3. Estimated weights for variables related to benefits and costs of fire suppression from a linear probability model estimated with five distributed spatial leads restricted using quadratic Almon weights, with housing variables drawn from county assessors' data

	Spatial leads					
Variable	m	$m+1$	$m+2$	$m+3$	$m+4$	$m+5$
(No. of res. props. > 0)	.053	.028	.01	-.0013	-.0064	-.005
	(.034)	(.018)	(.015)	(.015)	(.013)	(.018)
No. of res. props.	.00056	.00041	.00033	.0003	.00033	.00042
	(.00042)	(.00027)	(.0002)	(.00015)	(.000088)	(.00018)
Avg. value of res. props.	.2	.15	.12	.08	.049	.022
	(.095)	(.051)	(.055)	(.057)	(.046)	(.065)
Total value of res. props.	.00043	-.0013	-.0024	-.0029	-.0028	-.0021
	(.0024)	(.0014)	(.001)	(.0008)	(.00065)	(.0013)
Topographic ruggedness index	-.0039	.00039	.000015	-.00015	-.0001	.00015
	(.00079)	(.00018)	(.000085)	(.00011)	(.00005)	(.00017)
Pct. < 0.5 km from road	.00045	-.00046	-.00012	.000034	7.1e-06	-.0002
	(.00022)	(.00016)	(.000068)	(.00007)	(.000054)	(.000087)
Ln($\Delta 1$)	.095					
	(.095)					
Ln(Intensity)	.096					
	(.096)					
Contains major road	.19					
	(.19)					
ΔT missing	.36					
	(.36)					
Fire fixed effects	Yes					
No. of obs.	10,861					
No. of fires	178					

Note: All models include distance from ignition fixed effects. Standard errors are in parentheses and are clustered by fire.

Table A4. Estimated weights for variables related to benefits and costs of fire suppression from a linear probability model estimated with five distributed spatial leads restricted using quadratic Almon weights, with proxies for housing from US Census data

	Spatial leads					
Variable	m	$m+1$	$m+2$	$m+3$	$m+4$	$m+5$
(No. of HU > 0)	.05	.017	-.003	-.0097	-.003	.017
	(.0083)	(.004)	(.0041)	(.0041)	(.0034)	(.0069)
No. of HU	.00041	.00024	.00011	.000032	5.8e-07	.000016
	(.00012)	(.000058)	(.000031)	(.000027)	(.000021)	(.000039)
Per capita income	.00024	.0002	.00016	.00014	.00014	.00014
	(.00027)	(.00012)	(.00011)	(.00012)	(.0001)	(.0002)
No. of HU $\times$ per capita income	-.0013	-.0025	-.0029	-.0024	-.0012	.00085
	(.0028)	(.0015)	(.00097)	(.00085)	(.00065)	(.0013)
Topographic ruggedness index	-.00015	-.000065	-.00007	-.000063	-.000044	-.000013
	(.000091)	(.000054)	(.000027)	(.000023)	(.000018)	(.000025)
Pct. < 0.5 km from road	.00099	-.00029	-.000088	.000018	.000031	-.00005
	(.000091)	(.000056)	(.000024)	(.000024)	(.000019)	(.000032)
Ln($\Delta 1$)	.12					
	(.12)					
Ln(Intensity)	.11					
	(.11)					
Contains major road	.16					
	(.16)					
ΔT missing	.5					
	(.5)					
Fire fixed effects	Yes					
No. of obs.	86,990					
No. of fires	1,499					

Note: All models include distance from ignition fixed effects. Standard errors are in parentheses and are clustered by fire. HU refers to housing units.