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

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Abstract: Costs of fighting wildfires have increased substantially over the past several decades. Yet surprisingly little is known about the effectiveness of wildfire suppression or how wildfire incident managers prioritize resources threatened within a wildfire incident. We investigate the determinants of wildfire suppression effort using a novel empirical strategy comparing over 1,400 historical fire perimeters to the spatial distribution of assets at risk. We find that fires are more likely to stop spreading as they approach homes, particularly when homes are of greater value. This effect persists after controlling for physical factors (fuels, landscape, and weather) using a state-of-the-art wildfire simulation tool. As well, the probability that spread will be halted is affected by characteristics of homes 1–2 kilometers beyond a fire's edge. Overall, we find that suppression efforts can substantively affect wildfire outcomes but that some groups may benefit more from wildfire management than others.

JEL Codes: H41, Q28, Q54

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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 the severe 2020 and 2021 fire seasons, 2018's Camp Fire, and 2017's wine country fires. Fires can become large disaster events that kill firefighters

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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 (Cook and Becker 2017; National Interagency Fire Center 2020).[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 is highly effective when firefighters are 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. Moreover, while empirical evidence (discussed below) 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 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.

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). These results cannot be interpreted 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 even find a positive correlation between

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

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] In addition, because these studies 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 priorities and effectiveness from observed patterns of wildfire spread across the landscape. First, we develop a simple spatial-dynamic theory of wildfire suppression decision making 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 1,435 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 combined effects of landscape, fuels, and wind 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 (USFS) and is used in the management of wildfire incidents. MTT integrates data on topography, fuels, 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 expected to be similar but assets at risk are different, thereby attributing the effects of assets at risk to suppression effort on behalf of those assets.

The approach resolves several challenges in the empirical analysis of wildfire suppression decision making. 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

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.

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 model 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., Maantay and Maroko 2009; Cutter 2012; 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., Achen and Bartels 2004; Healy and Malhotra 2009). 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 of individual fire incidents in an explicitly spatial-dynamic manner.

1. THE WILDFIRE SUPPRESSION DECISION ENVIRONMENT

Fire managers operate within a highly complex decision-making 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

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

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 have a high degree of discretion to make strategic decisions to minimize losses.

Fire suppression proceeds in several phases as fires grow larger. 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, in which a larger number of resources and control tactics are applied to the fire. Fires that continue to spread may become Type 2 or Type 1 incidents, which involve fire management teams with progressively greater numbers of personnel and resources.

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 suppression 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 "back-burning," which involves taking advantage

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.

of favorable wind conditions and setting fire to fuels in the main fire's path. Fire managers can also take advantage of preexisting fuel breaks, such as roads.

Fire management teams are led by an incident commander (IC), who leads implementation of planning and operations on the incident. A fire's IC may change as the incident's size and complexity escalate. Each IC is given authority to manage a fire by an "agency administrator"—the highest ranking official responsible for management in the area of the fire—through a written delegation of authority, which conveys expectations, overall strategy, and goals but is broad enough to allow flexibility given contingencies that may arise during the incident.[5] The IC is then responsible for implementing tactics consistent with the incident's strategy and goals. Because agency administrators and incident commanders are jointly responsible for shaping management priorities and allocation of suppression resources during an incident, and because our theoretical and empirical models do not distinguish between these roles, we refer to incident commanders and agency administrators together as "fire managers," consistent with previous literature (e.g., Wilson et al. 2011; Calkin et al. 2012; Bayham and Yoder 2020).[6]

In choosing how to deploy suppression resources, fire managers face a complex set of loosely defined incentives. Managers do not own the assets they are charged with protecting. Therefore, their decision making 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). Despite the complexity of the incentives facing fire managers, studies in the fire management literature typically assume that fire managers choose strategies to minimize the sum of expected wildfire damages and suppression costs (Sparhawk 1925; Donovan and Rideout 2003). In our empirical analysis, we use a flexible approach that avoids 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

5. Agency administrators may be federal officials (e.g., USFS forest supervisors, Bureau of Land Management district managers, and National Park Service park superintendents), state officials (e.g., state forest officers), or local officials (e.g., local fire chiefs).

6. For a more complex model of fire management decision making meant to take into account fire command structure and resource allocation decision making across fires, readers can see Bayham and Yoder (2020).

software, including FARSITE (Finney 1998) and FSPro (Finney et al. 2011), developed to aid fire management decision making. 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 our empirical work, we use fire simulation models to help control for effects of spatial variation in fuels and topography on wildfire spread.

2. THEORY

In this section, we use a simplified model of fire management decision making to highlight several important features of the fire managers' decision environment described in the previous section. The model emphasizes the problem's spatial-dynamic nature and the role that uncertainty plays. As well, the structure of the model motivates the design of our empirical analysis, which draws inferences about fire suppression priorities and effectiveness from observed fire spread distances within discrete directions of spread.

We begin by assuming that fire ignition occurs at a randomly chosen origin in space at time $t = 0$. We assume that fires spread in L discrete directions, indexed by l, from their origin. Discrete locations s distance from the origin in each direction are denoted (s, l). Over time, the fire burns in each direction until it is extinguished in location $\bar{s}_l$, beyond which no further burning occurs. As a result of the fire, all built and natural assets lying from the point of ignition through location $\bar{s}_l$ are lost to fire.[7] This formulation allows us to characterize final fire perimeters of a variety of shapes, while avoiding the complexities of fire spread in multiple directions beyond the ignition point.

At each point in time, the state of the system is characterized by how far the fire has advanced from the ignition point. The state variable, d_{lt}, is the farthest location s from the ignition in direction l that is burning in time t. With probability λ_{sl} the fire will be extinguished and the state variable will equal $\bar{s}_l$, whereas with probability $1 - \lambda_{sl}$ the fire will spread to location $(s + 1, l)$. Thus, the state variable evolves according to:

$$d_{t+1,l} = \begin{cases} d_{lt} \equiv \bar{s}_l, & \text{with probability } \lambda_{sl} \\ d_{lt} + 1, & \text{with probability } 1 - \lambda_{sl} \end{cases} \tag{1}$$

if $d_{lt} \neq \bar{s}_l$. When the fire is extinguished in location $\bar{s}_l$, d_{lt} enters an absorptive state and remains at $\bar{s}_l$ in all future time periods. The vector $D_t = (d_{1,t}, d_{2,t}, \ldots, d_{L,t})$ defines the state of the system in t and $\bar{S} = (\bar{s}_1, \bar{s}_2, \ldots, \bar{s}_L)$ defines the final fire perimeter.

7. We make this assumption in the theoretical model for simplicity and because our wildfire perimeter data do not provide detailed data on structure loss. Our empirical model does not assume that all assets in the fire's path are lost, nor does it rule out ecological benefits of wildland fire, such as fuel reduction.

In this simple framework, for a given ignition, the realized fire perimeter $\bar{S}$ is a random variable governed by λ_{sl}, the probability the fire will stop its spread in a given location. We define λ_{sl} according to the function $\lambda(w_{sl}, z_{slt})$, where w_{sl} is a vector of location-specific characteristics which impact the ease of suppression, including characteristics of the natural and constructed landscapes (e.g., topography, fuels, roads), as well as the wind direction relative to fire spread direction l, and z_{slt} represents the resources allocated to suppress the fire at (s, l) as of period t. The landscape is also characterized by a vector of assets, both constructed (x_{sl}^B) and natural (x_{sl}^N), that are at risk from fire at each location. Damages associated with asset loss due to the burning of a given location are given by the damage function $\psi(x_{sl}^B, x_{sl}^N)$.

The fire manager's problem is to choose in each period how to allocate fixed resources across locations to minimize the expected total damages across the fire's lifetime.[8] In each time period, the manager can allocate resources to any location (s, l). Thus, the resource allocation for time period t is given by the matrix $\mathbf{R}_t$ with element r_{slt}.[9] While this general formulation simplifies notation, it would never be optimal for a manager to devote new suppression resources in a location that has already burned or in a direction in which the fire has been extinguished. However, it may be optimal for the manager to allocate resources in advance of the fire—namely, in a location that lies beyond d_{lt}—given the dynamics inherent in the problem. Moreover, resources allocated previously are assumed to be effective at suppressing the fire when it arrives. This feature of the model is consistent with the frequent use of indirect control tactics ahead of the fire line (e.g., back-burning; see sec. 1).

Because suppression resources may be allocated at a given location more than once, we represent the effective cumulative suppression effort across the landscape with the matrix $\mathbf{Z}_t$, with element z_{slt}; $\mathbf{Z}_t$ evolves according to:

$$\mathbf{Z}_t = \mathbf{Z}_{t-1} + \mathbf{C} \circ \mathbf{R}_t, \tag{2}$$

where $\mathbf{C}$ is a matrix with element c_{sl} measuring the effectiveness of suppression resources at any location around the fire (i.e., the location-specific cost of a unit of suppression effort), and $\mathbf{C}$ multiplies $\mathbf{R}_t$ element-wise to result in a matrix of suppression effort inputs in period t. The allocation $\mathbf{R}_t$ is subject to a period-specific resource constraint: $\Sigma_s \Sigma_l r_{slt} \leq \bar{R}_t \;\; \forall \;\; t$. The resource constraint says that in any time period total resources allocated across the fire must not be greater than available resources (e.g., available personnel and equipment).

8. See Bayham and Yoder (2020) for a more complex formulation in which the resource constraint for an individual fire is determined as the solution to a loss minimization problem across the set of active wildfires.

9. The term $\mathbf{R}_t$ has dimension $L \times s_{\max}$ where $s_{\max}$ is an arbitrarily large distance from the ignition point.

The fire manager's problem is to solve the following dynamic program in discrete time:

$$V_t(D_t, \mathbf{Z}_t) = \min_{\mathbf{R}_t} \sum_{l \in \tilde{D}_t} [1 - \lambda(w_{tl}, z_{tl})]\psi(x_{tl}^B, x_{tl}^N) + E_{t+1}[V_{t+1}(D_{t+1}, \mathbf{Z}_{t+1})|\mathbf{R}_t], \quad (3)$$

subject to the state equations in (1) and (2) and the available resources $\bar{R}_t \; \forall \; t$. The term $\tilde{D}_t$ denotes the set of directions in which the fire is burning in time t and E_{t+1} is the expectations operator conditional on information and allocation of resources in time t. The notation in (3) is simplified by the fact that, because the fire extends one distance interval each time period until extinguished, distance from the ignition point is equivalent to time while the fire is still burning in a given direction. This means that current damages across unsuppressed directions, the first term in equation (3), can be written in terms of the time period t, since the distance s is redundant. As well, it means $\tilde{D}_t$ can be defined as the subset of D_t in which $d_{lt} = t$, since the fire either continues to spread or is extinguished in each period. The second term captures expected future losses given this period's allocation of resources.

The problem implies that damage-minimizing fire managers will allocate fire suppression according to a policy function, $\mathbf{R}_t^*(D_t, \mathbf{Z}_t)$. Additionally, effort depends implicitly on the parameters of the problem (the $L \times \bar{s}_{\max}$ matrices $\mathbf{X}^B$, $\mathbf{X}^N$, $\mathbf{W}$, and $\mathbf{C}$, with elements x_{sl}^B, x_{sl}^N, w_{sl}, and c_{sl}, respectively); fire managers will allocate suppression effort as a function of the state variables, and as a function of costs and benefits of suppression in any location (s, l). Notably, benefits of fire extinction at location (s, l) may include avoided losses to assets at that location and assets farther in direction l, which are no longer threatened if the fire is extinguished in location (s, l).

While analyzing the precise analytical or numerical solutions to this high-dimensional dynamic programming problem is beyond the scope of this work, the model identifies four key features of the fire manager's problem that must be addressed in our empirical work:

1. Wildfire suppression is inherently spatial in nature.
2. The process is dynamic, and resource allocations will respond not only to assets that are immediately at risk but also to those resources that potentially lie along the fire's future path.
3. Potential for suppression is impacted by the spatial distribution of both constructed and natural attributes of the landscape as well as wind direction.
4. Because suppression effort will be affected by assets at risk (natural and constructed) as well as landscape features that impact probability of suppression, any analysis that attempts to assess the effect of constructed assets on fire suppression efforts must effectively control for correlations between natural assets, landscape features that impact suppression probability, and said constructed assets.

The empirical model that we develop below is specifically tailored to address each of these four concerns.

3. EMPIRICAL MODEL

3.1. Fire Spread Distance as Duration

The theory developed in the previous section suggests the logic of duration analysis and thus motivates our empirical approach. Typically, duration analysis is used to model the length of time between transitions across states to draw inferences about factors that affect the transition. For example, an econometrician may observe information about unemployment durations and use these data, along with individual and time-varying covariates, to understand factors that affect the likelihood that individuals will become employed. In our case, we observe fire spread distances ($\bar{s}$). Based on our theory, 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, the theory suggests a parallel between fire spread distances and durations, and we apply tools from duration analysis to draw inferences from fire spread distances regarding the effects of suppression effort and natural factors on fire extinction probabilities.[10]

Adopting the notation from the previous section, we model the extinction probability within a given location as depending on physical landscape characteristics and wind (w) and fire suppression effort (z). The extinction probability, or the probability that a fire is extinguished distance s in direction l from its ignition point, conditional on it not yet having been extinguished, then can be written:

$$\Pr(y_{sl} = 1 | y_{s-1,l} = 0, s \leq \bar{s}_{\max}) = F(w_{sl}, z_{sl}; \theta), \tag{4}$$

where θ is a vector of parameters, and $y_{sl} \equiv \mathbf{1}(d_{sl} = \bar{s}_l)$,

For each location, we define ω_{sl} to be a vector containing w_{sl} and z_{sl}. We assume that conditional on the vector ω_{sl}, (i) the probability that the fire is extinguished is independent across locations within a single direction of spread and (ii) the probability that the fire is extinguished is independent across directions of spread. The assumption that probability of extinction is independent across directions of spread 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 3.3, we discuss how we test the model's robustness to nonindependence among fire spread directions. For now, we maintain this assumption and use it to write the overall likelihood function over L directions of spread and K fires as:

$$\mathcal{L} = \prod_{k=1}^{K}\prod_{l=1}^{L}\prod_{s=1}^{\bar{s}_l} F(\boldsymbol{\omega}_{sl}; \theta)^{y_{slk}} (1 - F(\boldsymbol{\omega}_{sl}; \theta))^{(1-y_{slk})}, \tag{5}$$

10. Previous work by Bayham (2013) and Bayham and Yoder (2012) also applied duration analysis to fire spread.

where the first term represents the probability that the fire will stop burning at location (s, l), the second term represents the probability that the fire continues to burn in each of the locations prior to location (s, l), and each direction of spread l on each fire k is described by $\bar{s}_l$ observations.[11]

This model corresponds to "grouped" or discrete time duration models (Sueyoshi 1995). The likelihood function is the same form as the likelihood function of a standard binary response model, and the particular binary response model to be estimated depends on the specification of the instantaneous hazard function. Given the common assumption of an underlying continuous time exponential proportional hazard function, the corresponding grouped duration model is estimated with a complementary log-log model with distance-interval fixed effects (Jenkins 1995). This is the binary response model we estimate in our primary specifications.[12]

3.2. Specification of Spread-Distance Model

We specify the probability that fire stops burning in location (s, l), conditional on not yet having been extinguished in location $(s - 1, l)$, as:

$$F(\boldsymbol{\omega}_{s,l}; \theta) = F(w_{sl} + z_{sl} + \mu_s), \tag{6}$$

where w_{sl} and z_{sl} are linear indices representing the effects of physical factors and suppression effort, respectively, on fire extinction, and μ_s are a set of distance from ignition fixed effects.[13]

The index w_{sl} accounts for a variety of physical factors—including topography, fuel availability and conditions, and wind—that can interact in complex ways to affect fire spread. We define the index as $w_{sl} \equiv \mathbf{v}'_{sl}\gamma$, where the vector $\mathbf{v}_{sl}$ includes outputs from a US Forest Service fire simulation tool that we will describe in detail in the following section, as well as several separately assembled control variables.

The linear index z_{sl} represents fire suppression effort at location (s, l). Spatially varying data on within-fire allocation of suppression effort are unavailable; however, the theory provides guidance about how to proxy for effort. The theory implies that total suppression z_{sl} allocated to location (s, l) equals $\Sigma_{v=0}^{t} r^*_{vl}$, where damage-minimizing fire managers allocate suppression effort according to a policy function $R^*(D_t, \mathbf{Z}_t)$ that equates marginal benefits and marginal costs of suppression effort in the location. Benefits are a

11. The dependent variable $y_{s,l} = 0$ for all observations such that $s < \bar{s}_l$; $y_{s,l} = 1$ for the final sector burnt in each direction l.

12. In the appendix, we also test alternative binary response models.

13. In proportional hazard models, hazard probability is proportional to some function of time. In grouped duration models, this assumption yields time fixed effects, which allow separate intercepts in each time interval. Here, we include analogous distance from ignition fixed effects, which are important in this application because fires that grow large are more likely to continue to spread.

function of assets protected by suppression, including assets at the fire's current location and, potentially, assets that are protected by suppression of the fire at that location but located farther in the direction of spread. 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 use observable factors that affect the costs and benefits of fire suppression in a given location as a proxy for effort, and we write total allocated effort z_{sl} as:

$$z_{sl} \equiv \sum_{\nu=s}^{\bar{\nu}} \mathbf{x}'_{s+\nu,l}\beta^{\nu} + \mathbf{c}'_{s+\nu,l}\delta^{\nu}, \tag{7}$$

where benefits and costs of suppression in location (s, l) are described by vectors $\mathbf{x}_{s,l}$ of assets at risk (including both constructed assets $\mathbf{x}^{B}_{s,l}$ and natural assets $\mathbf{x}^{N}_{s,l}$) and $\mathbf{c}_{sl}$ of factors affecting costs, corresponding to variables from section 2.

Suppression effort is specified as a function of "spatial leads" of benefits and costs of suppression up to $\bar{\nu}$ sectors away. We anticipate that the spatial leads will be highly correlated with one another; a sector that contains many homes is likely to be near other sectors with many homes. Therefore, as is typical of distributed lag models, estimates of lead effects may be imprecise and unreliable. To improve estimates of spatial leads we smooth coefficients using a restricted distributed lead model. Specifically, following Almon (1965), we assume that spatial weights are given by a polynomial function, where each spatial lead coefficient is defined as $\beta^{\nu} = \sum_{\tau=0}^{\bar{\tau}} a_{\tau}\nu^{\tau}$.[14]

3.3. 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 in an area might be correlated with presence of fuels. 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.

14. We modify the Almon weighting scheme slightly for effort variables representing factors correlated with costs (e.g., percentage of sector accessible by road). When a fire reaches a given sector, 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 sector than within lead sectors, we relax the restrictions of the Almon and linear weighting schemes for reference sector cost coefficients. 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.

As indicated earlier, the assumption that extinction probabilities are independent across directions of spread is likely false. As derivation of equation (5) 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 (6). 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 (6). 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 (6). 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).

4. 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.

4.1. Wildfire Data

Data describing areas burned come from the Monitoring Trends in Burn Severity (MTBS) project (MTBS 2014). The MTBS project uses Landsat satellite imagery to map the geographic extent of all fires greater than 1,000 acres in size in the western United States since 1984. Wildfire hazard is a significant concern in this region, and fire regimes in the western states are distinct from those in the East. This size threshold for the MTBS data means that our results on suppression effort should be viewed as representative of fires that escape initial containment and grow to be relatively large.[15] MTBS data reflect final

15. 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.

fire perimeters and do not provide detail about fire spread during the course of an incident; thus, we base our analysis of fire spread on spatially but not time-varying variables.

Ignition locations are from the US Forest Service 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 at least 1 kilometer (km).[16] We focus on fires in 1999–2015 whose ignitions were within 10 km of the wildland urban interface.[17] 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 communities with varying characteristics, which is captured in this set of fires. 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, since our empirical strategy requires a single ignition point.

The remaining 1,435 fire ignitions, the locations of which are shown in figure B.1 (figs. B.1, B.2 are available online), constitute 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 measure assets at risk using assessors' data on housing locations and values, and we use a different sample when using assessors' data. Characteristics of fires in the census and assessors' samples are described in table B.1 (tables B.1–B.10 are available online). In most respects, fires in the two samples are similar, although fires in Arizona, California, and Washington, and fires on US Forest Service land are somewhat overrepresented in the assessors' sample. As well, because the assessors' data sample includes only fires after the assessment date, it includes only fires from the 2011–15 period, whereas the census sample includes fires from earlier periods as well. The "All fires" column in table B.1 includes all fire ignitions in the 11 contiguous western states, 1999–2015. With the exception of fire size, characteristics of these fires, including causes, are broadly similar to characteristics of fires in the census and assessors' data samples. The vast majority of fires are extinguished before they grow large; therefore, the "All fires" column includes far more fires smaller than 1,000 acres.

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16. Inaccuracies in ignition locations would be a concern if our results were driven by very small fires. In appendix (table B.6), we show that we obtain similar results when we restrict our sample to only fires larger 5,000 acres.

17. 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 United States at the US census block level.

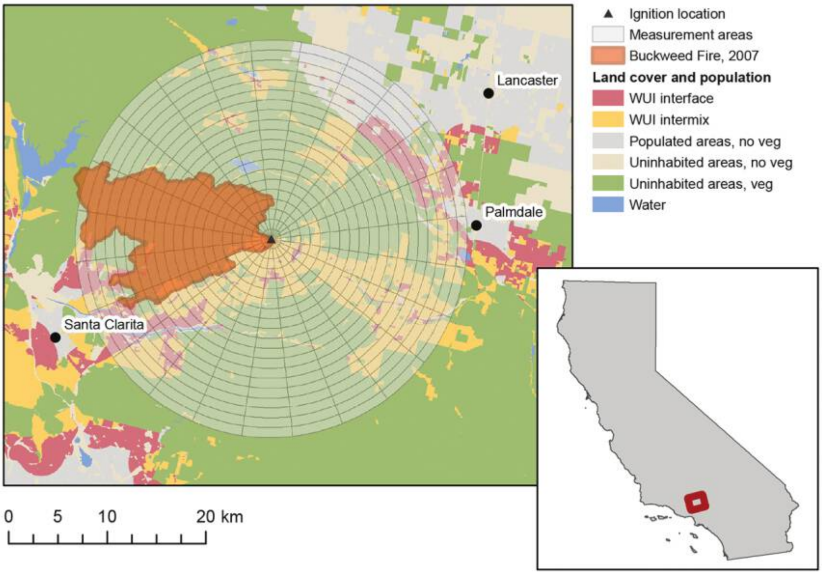

Figure 1. Illustration describing the construction of the data set. The landscape surrounding each ignition point is divided into 24 discrete directions of spread. Each direction of spread is divided into 1 km distance intervals, up to a maximum distance of 20 km, yielding a circular grid surrounding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

Together, fire ignitions and fire perimeters define fire spread distances ($\bar{s}_l$), which we use to study factors that affect the likelihood of fire extinction at any given location. To adapt the theoretical and empirical models to the data, we divide the area surrounding each wildfire ignition point into 24 directions of spread (L), each with a central angle of 15 degrees.[18] We further divide each direction of spread into distance intervals of 1 km, up to a maximum distance ($\bar{s}_{\max}$) of 20 km, creating a circular grid surrounding each ignition, where each location (s, l) is defined by a given sector of the grid. An example is provided by figure 1. We overlay the circular grid with the corresponding wildfire perimeter and code the fire as being extinguished ($y_{sl} = 1$) within a sector if the fire fails to reach a sector's centroid ($d_{sl} = \bar{s}_l$).[19] We code all prior sectors ($d_{sl} < \bar{s}_l$) within the direction of spread as burnt ($y_{sl} = 0$). Since we estimate the probability that fire stops burning conditional on not yet having stopped burning, we drop all observations in each direction the fire is first extinguished in that direction. Therefore, our final data set consists of a set of a maximum of 480 observations for each fire, with each one corresponding

18. We check for robustness of our results to varying values of L.

19. Coding sectors as burnt if the fire burns any portion of the interval does not substantively change the results.

to a circular sector. For any given fire, the actual number of observations in the data set for each fire depends on how far the fire burned in each direction.

Fires sometimes spread in irregular nonconvex 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.[20] Figure B.2 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.

4.2. 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. Table 1 provides a list of variables we use to account for spatial variation in benefits and costs of fire 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 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 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. 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

20. An alternative would be to code y_{sl} as 0 until the fire is finally extinguished within direction l. Applying this alternative coding scheme does not substantively change the results.

assessors' data, we limit the sample to the 171 fires indicated by triangular markers in figure B.1.[21]

As is clear from figure 1, the circular sectors 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 sector.

Within models using census data, we use the total number of housing units as a proxy for the number of homes in a sector. As a proxy for the total value of homes within each sector, we use the total number of housing units multiplied by per capita income.[22] To allow for the possibility that fire managers undertake greater suppression efforts on behalf of higher-income residents, we also include per capita income. To understand potential differences among property types, we use census vacancy status data to calculate the number of vacation housing units in each sector as the percentage of total housing units in the sector that are vacant, seasonally occupied housing units. We also use census tenure data to calculate the percentage of rental properties in each sector. 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.[23]

For models using assessor data, we measure analogous variables for each sector: number of residential properties, average value of residential properties, and total value of residential properties. More important than the value of residential properties within a sector 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.

Proxies for benefits by distance from the ignition point are summarized in the first panel of table 2; analogous variables based on assessors' data are summarized in the second panel. There is a clear trend in housing density (as well as total value of residential

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

22. 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 sector, including the number of homes rather than the housing density has a minor effect on results.

23. The assessors' data set contains no demographic data.

Table 1. Variable Definitions and Sources

Variable Name	Description	Source
	Benefit Variables/Assets at Risk	
No. res. props	Number of residential properties	CoreLogic, Inc.
Value res. props.	Average assessed value of residential properties (millions USD)	CoreLogic, Inc.
No. HU	Number of housing units within cell	US Census Bureau
Per cap. income	Per capita income (thousands USD)	US Census Bureau
Watershed importance	Watershed importance rating (0–100), times cell area	USFS Forests to Faucets Dataset
TES habitat	Total cell area classified as threatened or endangered species habitat	USFWS Threatened and Endangered Species Active Critical Habitat Report
Wilderness	= 1 if cell intersects areas in the National Wilderness Preservation System, = 0 otherwise	University of Montana Wilderness Institute and the BLM, USFWS, USFS, and NPS
Campgrounds	= 1 if cell contains federal, state, county, or city campgrounds, = 0 otherwise	Federal, state, county, and city campground data, compiled by Hillegas (2021)

	Cost Variables	
Topographic ruggedness index	Root mean square deviation of elevation within cell, times cell area	USGS 3D Elevation Program
Area < .5 km from road	Area of cell within .5 km of roads	USGS National Transportation Dataset and US Forest Service National Forest System Roads database
	Fire Spread Variables	
ΔT	Difference in simulated time of fire arrival between the current cell and previous cell in the same direction of spread (hours)	MTT fire simulations
ΔT missing	$= 1$ if ΔT is missing,[a] $= 0$ otherwise	MTT fire simulations
Intensity	Log of simulated fire intensity (kW/hour)	MTT fire simulations
Contains major road	$= 1$ if cell contains a primary or secondary road, $= 0$ otherwise	US Geologic Survey National Transportation Dataset
Wind difference	Cosine(direction of spread minus dominant wind direction), ranges from –1 to 1; higher values indicate fire is spreading against the wind	RAWS USA Climate Archive

Note. USFS = US Forest Service; USFWS = US Fish and Wildlife Service; BLM = Bureau of Land Management; NPS = National Park Service; USGS = Geological Survey; MTT = minimum travel time; RAWS = remote automated weather station.

[a] ΔT may be missing because either the focal cell or previous cell is missing fuels in the majority of its area or because time of arrival is predicted to be lower in the focal cell than the previous cell.

Table 2. Summary Statistics for Circular Grid Cell–Level Observations, by Distance from Fire Ignition Point

	0–5 km (1)	5–10 km (2)	10–15 km (3)	15–20 km (4)	Whole Sample (5)
	I. Full Sample				
Benefit variables:					
(No. HU > 0)	.546	.618	.656	.682	.625
No. HU	4.18	19.7	38.5	62.8	31.1
HU density (HU/sq. km)	5.43	9.92	11.7	13.7	10.2
Per cap. income (thousands USD)	25.4	25.5	25.5	25.5	25.5
No. HU × per cap. inc. (millions USD)	.136	.596	1.18	1.9	.948
Other values at risk:					
Avg. watershed importance	29.8	29.7	29.7	29.5	29.7
TES habitat	11.9	10.7	9.82	9.28	10.4
Wilderness	.0666	.0744	.0817	.0874	.0775
Campgrounds	.00214	.00561	.0081	.0107	.00661
Cost variables:					
Avg. topographic ruggedness index	19.6	17.7	17.4	16.7	17.9
Pct. < 0.5 km from road	59.5	59.6	58.9	58.3	59.1
Fire spread variables:					
T (hours since ignition)	52.4	124	194	208	142
ΔT	16.5	14.3	14.2	14.1	14.9
ΔT missing	.154	.221	.247	.411	.258
Intensity	278	303	299	295	294
Contains Major Road	.0715	.111	.15	.185	.129
Wind Difference	.000457	.000556	.0013	.000814	.000779
No. of observations	170,982	169,732	168,537	167,367	676,618
	II. 2011–15 Assessor's Data Sample				
(No. res. props. > 0)	.105	.18	.223	.251	.19
No. residential props.	2.28	13	30.3	42.3	22
No. res props./sq. km	2.82	6.5	9.24	9.2	6.94
Avg. value res. props. (millions USD)	.185	.181	.222	.263	.221
Total value res. props. (millions USD)	.316	1.68	4.35	7.63	3.49
No. of observations	20,391	20,358	20,351	20,350	81,450

properties) over distance from the ignition point. This is likely due to selection: a fire is more likely to grow to be large, and therefore be included in the sample, if it begins in a more rural location. This relationship suggests that, in estimating the effect of housing density 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, threatened and endangered species (TES) habitat, or recreation sites (e.g., campgrounds). We collected data describing the spatial distribution of these assets from a variety of sources described in table 1. The likelihood of the fire reaching a campground is increasing in distance from the ignition, similar to housing density. The same pattern is seen for wilderness areas, which may be related to lower rates of human-caused ignitions in remote, roadless areas.

To account for differences in the cost of fire suppression over space, we collected data on accessibility and topographic ruggedness, which affect the difficulty firefighters have in accessing a given location. 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 meter (m) scale across the landscape surrounding each ignition point (Riley 1999; Nunn and Puga 2012). We then averaged TRI within each circular sector and multiplied average TRI by sector area to capture increases in costs due to expansion of the affected area. We measured accessibility as the total area within each sector that is within 0.5 km of a road. Ruggedness declines somewhat in distance from the ignition point, but proximity to roads shows little change (table 2).

Another important factor affecting cost of effort is the availability of personnel and equipment resources. Since we lack data on the time fires reached each location on the landscape, we are unable to explicitly account for temporal variation in availability of firefighting resources. However, fire-level fixed effects will account for differences across fires in average national demand for and availability of resources.

4.3. 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 various fire simulation software programs (e.g., 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 decision making). 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 complex physical 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 (US Geological Survey 2014), which provides remotely sensed landscape data at a 30 m resolution.[24] 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).[25] More information about our MTT simulations and the input data we use is provided in the appendix (available online).

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. Therefore, 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.

For each of the 1,435 wildfires in the sample, we measure arrival time within circular sector (s, l), which we denote T_{sl}, as the time at which fire is expected to reach the centroid of the sector. 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 $\Delta T_{sl} = T_{sl} - T_{s-1,l}$,[26] and we use this discretized rate of spread between sectors as well as fire intensity as our primary predictors of the effects of physical factors on the probability

24. 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 2006–10, and 2010, 2012, and 2014 data for the two years following each of those updates.

25. 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.

26. For sectors such that $s = 1$, $\Delta T \equiv T_{sl}$.

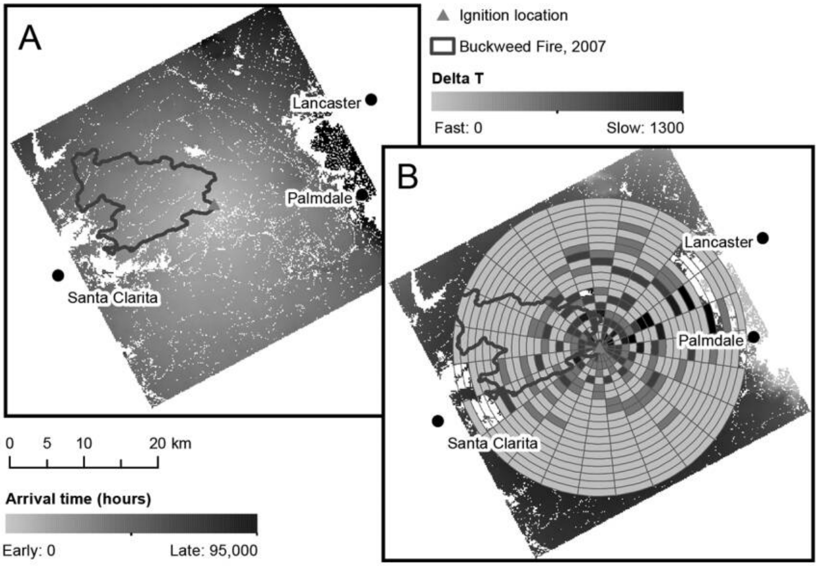

Figure 2. Illustration of fire simulation output. Color version available as an online enhancement

of fire extinction.[27] An example of MTT outputs is provided in figure 2. Figure 2*A* illustrates the surface of simulated arrival times across the landscape surrounding an example fire ignition. Figure 2*B* illustrates the outcome of averaging arrival times within sectors and taking differences across successive sectors.

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 sector as missing if fuel is absent for more than 50% of its Landfire pixels. 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 in equation (6), 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 sector lack fuel (ΔT missing). We account for wildfire intensity using $\ln(\text{Intensity} + 1)$. Further, we supplement MTT outputs with an indicator variable for whether a primary or secondary road crosses each sector, since roads provide a major barrier to fire spread that is not fully captured by MTT.

Because MTT accepts only a single wind direction and speed, it may not fully account for effects of wind on fire spread; therefore, in addition to including wind direction and speed in the fire simulations, we create a separate variable, called Wind Difference, based on the difference between fire spread direction and the dominant wind direction

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

in the week following each fire's ignition date. We calculate the dominant wind direction as the mean wind direction ($\bar{\theta}_k$, measured in radians) during hours in which wind speed was in the top quintile of wind speeds during the week.[28] Wind Difference is then calculated as the $\cos(\phi_l - \theta_k)$, where ϕ_l measures in radians the angle of direction of spread l. The variable ranges from −1 to 1; when wind is coming from the direction a fire is spreading toward, Wind Difference equals 1, and when wind is blowing in the direction of fire spread, it equals −1. Therefore, we expect the sign of the coefficient on Wind Difference to be positive.

Altogether, we specify the effects of physical factors on extinction probability through the function

$$\begin{aligned} w_{sl} = {} & \gamma_1 \ln \Delta(T_{sl} + 1) + \gamma_2 \ln(\text{Intensity}_{ml} + 1) \\ & + \gamma_3(\Delta T \text{ missing})_{sl} + \gamma_4 \text{Wind Difference}_{sl} + \gamma_5 \text{Major Road}_{sl}, \end{aligned} \tag{8}$$

where $\ln(\Delta T_{sl} + 1)$, and $\ln(\text{Intensity}_{sl} + 1)$ are coded as 0 if fuel is absent in location (s, l). Table 2 describes how Intensity, T, ΔT, and the fraction of sectors 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 ignition point, whereas the number of sectors 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, perhaps since these areas are more likely to include developed areas, whose fuels are not modeled.

5. RESULTS

5.1. Basic Specification

Our basic specification includes distance-from-ignition fixed effects and restricts attention to values at risk, cost factors, and fire spread variables at the fire's current point of spread. That is, we exclude spatial leads and restrict ν_0 and $\bar{\nu}$ within equation (6) to equal 0. We estimate equation (5) using a standard complementary log-log likelihood function (corresponding to an underlying exponential proportional hazard function) and report marginal effects calculated at variable means.

5.1.1. Estimates with Assessor Data

We begin with an analysis of the fire spread model using assessor data and the 2012–15 limited sample. Column 1 of table 3 includes only suppression-effort variables. Results

28. The mean wind direction $\bar{\theta}_k$ for fire k is calculated as the circular mean:

$$\bar{\theta}_k = \arctan 2\left(\frac{1}{N_h}\sum_{t=1}^{N_h}\sin\theta_{tk}, \frac{1}{N_h}\sum_{t=1}^{N_h}\cos\theta_{tk}\right),$$

where N_h is the number of hours that wind strength is in the top quintile in the week following ignition, and θ_{tk} is the wind direction. Both $\bar{\theta}_k$ and θ_{tk} are measured in radians.

Table 3. Results from Complementary Log-Log Regressions Using Assessors' Data

	(1)	(2)	(3)	(4)
(No. res. props. > 0)	.071†		.0075	.036
	[.042]		[.031]	[.038]
No. res. props.	.0015**		.0009	.0014**
	[.0005]		[.00074]	[.00046]
Avg. value res. props.	.22*		.29**	.29**
	[.11]		[.089]	[.099]
Total value res. props.	−.0043		−.00046	−.0047†
	[.0038]		[.0036]	[.0027]
TES habitat	.00029		.00079*	.00022
	[.00047]		[.00031]	[.00045]
Watershed importance	.00051		.0002	.0008†
	[.00047]		[.00049]	[.00045]
Campground	.16*		.077	.15*
	[.072]		[.08]	[.066]
Wilderness	.051		.08***	.044
	[.064]		[.026]	[.054]
Topographic ruggedness index	−.0046**		−.0085**	−.0059**
	[.00098]		[.00083]	[.00093]
Area < .5 km from road	.00052*		.00011	.00022
	[.00025]		[.00022]	[.00024]
Ln(ΔT + 1)		.085**	.033*	.079**
		[.017]	[.014]	[.017]
ΔT missing		.33**	.2**	.32**
		[.046]	[.039]	[.045]
Ln(Intensity)		.091**	.06**	.099**
		[.02]	[.012]	[.02]
Wind Difference		.066**	.045**	.068**
		[.018]	[.015]	[.018]
Contains Major Road		.19**	.19**	.18**
		[.035]	[.032]	[.035]
Fire fixed effects	Yes	Yes	No	Yes
No. of observations	10,801	10,801	10,801	10,801
No. of fires	171	171	171	171

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

† $p < .10$.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

suggest that fires are more likely to stop spreading in sectors containing a greater number of residential properties, especially when the average value of those properties is greater. Specifically, each $100,000 increase in the average property value increases the probability of extinction within the sector by 2.2 percentage points, compared with a baseline probability of 38%. Nonhousing assets at risk do not have strong effects, though we find that fires are more likely to stop at sectors containing campgrounds, which suggests suppression on behalf of recreation sites. Fires are also more likely to stop spreading in less rugged, more accessible sectors.

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 about 0.9 percentage points. When fire encounters a sector that has less than 50% of its area containing fuel, the probability that the fire stops spreading increases by 33 percentage points. Fires are more likely to stop spreading in sectors where they burn more intensely. While this result may seem counterintuitive, it may be that fires frequently stop their spread along ridgelines, where fire intensity also peaks. The positive coefficient on the wind difference variable indicates that the fire is more likely to be extinguished if it is spreading toward the direction from which the strongest winds are blowing, as expected. Finally, the probability of extinction also increases when the fire encounters a sector containing a major road or a sector where fuel is largely absent (in these sectors we cannot calculate a value for ΔT).

Column 3 includes both effort and fire spread variables. 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. The magnitude of the housing indicator variable declines substantially when fire spread variables are controlled for, suggesting that failing to account for effects of physical factors on fire spread may bias estimated effects of assets at risk.

Column 4 presents our preferred specification with fire fixed effects. These control 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 (with the exception of the housing indicator variable) 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.

5.1.2. Estimates with Census Data

Table 4 presents parallel results to table 3 using census data and the full set of 1,435 wildfires 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 sectors that

Table 4. Results from Complementary Log-Log Regressions Using Census Data

	(1)	(2)	(3)	(4)
(No. HU > 0)	.076**		.028**	.061**
	[.012]		[.011]	[.011]
No. HU	.0011**		.0011**	.00099*
	[.00042]		[.00026]	[.00042]
Per capita income (thousands USD)	.0014**		.00084*	.0009*
	[.00042]		[.00038]	[.00037]
No. HU × per cap. inc.	−.011		−.017**	−.011
	[.01]		[.0064]	[.0098]
TES habitat	−.00012		−.00014	−.00017
	[.00016]		[.00013]	[.00015]
Watershed importance	−.0001		−.00095**	−.00017
	[.00023]		[.00021]	[.00022]
Campground	.1**		.037	.059†
	[.033]		[.035]	[.033]
Wilderness	.02		−.014	.0096
	[.03]		[.017]	[.027]
Topographic ruggedness index	−.000011		−.00048	−.00012
	[.000066]		[.00035]	[.00011]
Area < .5 km from road	.0012**		.0011**	.00095**
	[.0001]		[.00011]	[.000094]
Ln(ΔT + 1)		.12**	.079**	.12**
		[.0065]	[.0059]	[.0065]
ΔT missing		.47**	.35**	.45**
		[.017]	[.017]	[.017]
Ln(Intensity)		.11**	.061**	.11**
		[.0076]	[.0044]	[.0075]
Wind Difference		.059**	.044**	.06**
		[.0061]	[.0049]	[.006]
Contains Major Road		.18**	.14**	.14**
		[.013]	[.013]	[.013]
Fire fixed effects	Yes	Yes	No	Yes
No. of observations	85,892	85,892	85,892	85,892
No. of fires	1,435	1,435	1,435	1,435

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

† $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

contain greater numbers of homes, especially if per capita income within the sector is greater. Table 4 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 sector.

In contrast to the marginal effect of property value reported in table 3, 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.[29] Yet, compared with the estimated 1 percentage point effect of a $10,000 increase in per capita income (table 4), table 3 indicates that the probability of extinction increases by nearly 3 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 sector are measured using census blocks, and estimates are quite similar to those obtained with assessor data, though they are measured more precisely.

In the appendix, we explore effects of additional census variables on probability of extinction. Table B.5 shows how probability of extinction varies across vacation and nonvacation housing units and by the percentage of properties that are rentals. We find that increases in the number of nonvacation housing units have a broadly similar effect on probability of extinction as housing units in table 4. In most specifications, increases in the number of vacation housing units have a larger effect on probability of extinction than increases in the number of nonvacation housing units. However, because we observe fewer vacation housing units, standard errors are somewhat larger and the effects of vacation housing units are not distinguishable from effects of nonvacation housing units. As well, we find weak evidence that probability of extinction increases with percentage renters, holding per capita income constant.

5.2. Specifications with Spatial Leads

For simplicity, the basic specification 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 valuable areas. In figure 3, we present results from ordinary least squares (OLS) models that set $\bar{\nu} = 5$ and therefore include spatial leads that account for anticipatory behavior among fire managers. Figures 3*a* and 3*b* illustrate distributed lead weights from models based on, respectively, assessors' data and census data. The Almon weighting specification assumes that spatial weights follow a quadratic function and that 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 B.7–B.10. As expected, weights generally decline with distance from the focal sector, falling to zero by a distance of approximately 3 km. Results are fairly similar

29. 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.

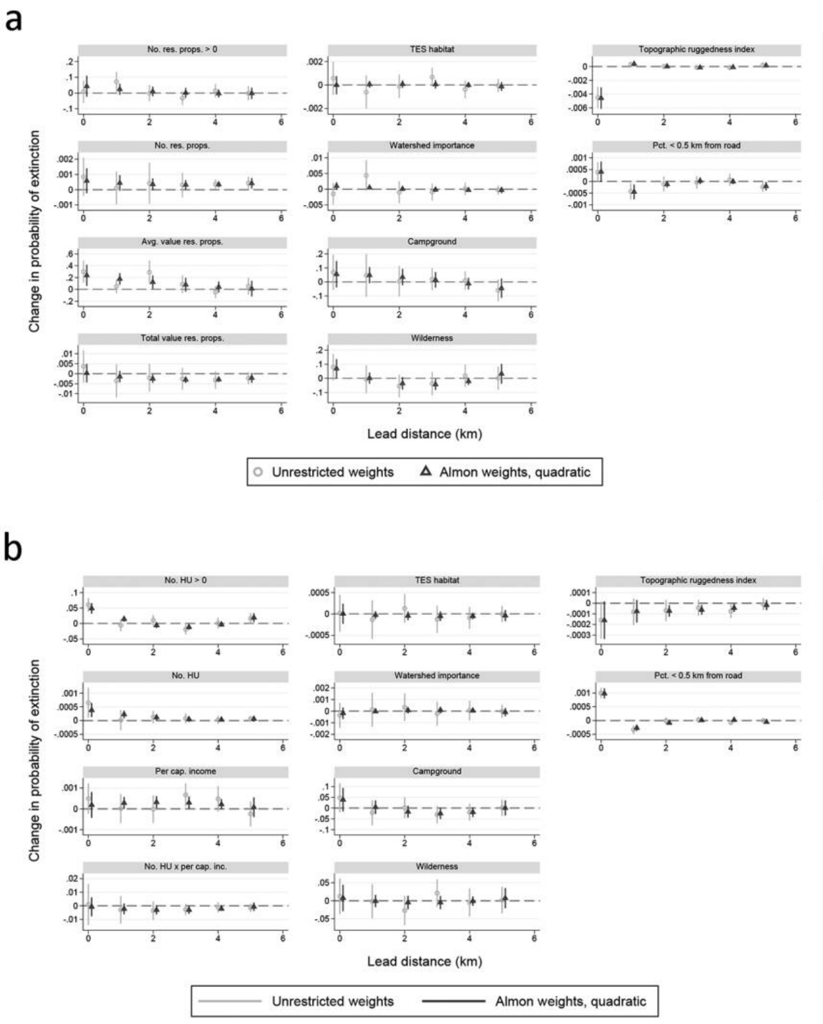

Figure 3. Weights estimated from distributed spatial lead models using housing variables from assessor's data (*a*) and census data (*b*). Color version available as an online enhancement.

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. Similar to previous results, fires are more likely to stop spreading as they approach sectors with residential properties, sectors with more homes, and sectors where those homes are worth more (or where per capita income is greater).

A possible concern with the results presented in tables 3 and 4 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 3 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.

5.3. Specification and Robustness Tests

Results of specification and robustness tests, described in section 3.3, are reported in appendix section B. We find evidence that the assumption of independent discrete directions of spread does not substantially bias our estimates. Further, our results do not change appreciably when we use alternative binary response models (e.g., logit, probit, LPM) in place of complementary log-log.

5.4. Scenario Analysis

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 sector. Estimates are based on the assessor data model with quadratic Almon weights. Scenario I shows the difference in probability of extinction when the sector 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 sectors. 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 6.1 percentage points above a baseline probability of 38%.

In scenario II, the initial number and value of properties is set at the mean values of 10 and $200,000, and we test the effects of a number of changes to housing within the sector. First, we increase the average value of properties within the sector 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 sector. 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 3 percentage points. Even when the number of properties decreases, increasing the average value of properties within a sector 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 sector by 10 homes no longer yields a statistically significant increase in the probability of extinction. However, increasing the

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.	Average Value of Res. Props. (Millions USD)	Total Value of Res. Props. (Millions USD)	ΔPr (y = 1)	SE
Scenario I. Initial values:	0	0	0		
A. Increase variables to mean within populated cells	10	.2	2	.06**	(.014)
Scenario II. Initial values:	10	.2	2		
A. Increase average value while holding no. props. constant	10	.4	4	.033**	(.0098)
B. Increase no. props. while holding average value constant	20	.2	4	.0015**	(.00064)
C. Increase average value while holding total value constant	5	.4	2	.033**	(.0097)
Scenario III. Initial values:	20	.3	6		
A. Increase average value while holding no. props. constant	20	.5	10	.03**	(.01)
B. Increase no. props. while holding average value constant	30	.3	9	−.000012	(.0019)
C. Increase average value while holding total value constant	12	.5	6	.032**	(.0097)

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.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

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 fig. 3*a*), which implies a diminishing effect of property value on the probability of extinction as the number of residential properties increases.

6. DISCUSSION

Federal expenditures on fire suppression reached $3.14 billion in 2018, a fourfold real increase compared with 1985–89 (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. This increase in wildfire activity is partly driven by climate change, which has substantially increased fuel aridity and the length of fire seasons across the western United States (Abatzoglou and Williams 2016) and which scientists expect to continue to drive severe wildfire seasons while fuels are not limiting (Liu et al. 2013). As well, climate-driven increases in wildfire activity are 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 fire extinction at a given point along an average fire's path through undeveloped terrain is roughly 38 percentage points, 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 (the average value) to $400,000, the probability of suppression increases by another 7.5%. 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 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 that fires spread linearly from their ignition points. While we believe that 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 monetary 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. Such a goal is obviously not stated policy, although decision making is subject to variety of bureaucratic incentives. In particular, fire management decision making may favor wealthier communities because of concerns among fire managers over political repercussions if such communities were to lose homes in a fire. Recent work by Anderson et al. (2020) finds that federal land management agencies are more likely to locate fuels treatments near communities with higher socioeconomic status and report suggestive evidence that this effect is due to greater political efficacy—that is, the ability of these communities to lobby for fuels treatments that reduce wildfire risk.

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 intensity and impacts can vary substantially between the ignition and the outer extent of fire spread. Not all structures within a fire perimeter are necessarily destroyed or even damaged, and 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). Still, it is reasonable to expect that properties inside a fire's perimeter are substantially more likely to incur damage.

Moreover, focusing on fire spread rather than structure loss buttresses our identification strategy. The identifying assumption 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.[30] Further supporting the idea that fire suppression drives the observed correlation

30. 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.

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 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. Our results show that firefighters show preference for protecting higher-valued homes and higher-income areas, adding to studies examining the potential for inequities in education, legislative responsiveness, and environmental policy outcomes (Meier et al. 1999; Butler and Broockman 2011; Fowlie et al. 2012). 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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