Endogenous adaptation to natural disasters: Wildfires and wildfire suppression

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Abstract

The evolution of risk under climate change depends both on how altered natural systems affect hazards and how humans respond. To evaluate endogenous adaptation to wildfire risk we estimate an empirical model of wildfire management that identifies the effect of threatened resources on wildfire suppression. Working with a state-of-the-art wildfire simulation tool we pilot the synthesis of ecological and economic models for improved environmental risk assessment. Results of this analysis highlight the importance of ecological processes and endogenous suppression responses for the housing stock (quantities and values) and for predicting potential property losses from climate-driven increases in wildfire hazard.

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The effects of climate change on physical, biological, and human systems are expected to become more severe in the coming decades, increasing risks to human health and well-being (Pachauri et al., 2014). Damages from wildfires and floods, heat-related mortality, and the spread of vector- and water-borne diseases are some of the anticipated impacts. Understanding and predicting climate-driven changes in risk is critical for many sectors of the economy, including insurance, real estate, and health care, in addition to government programs, policies, and infrastructure investments.

How risks evolve under climate change will depend on how natural systems are altered, as well as on human behavioral responses. For example, increased wildfire activity in the western U.S. has been documented in recent decades, and attributed to changes in temperature, precipitation, and vegetation moisture (Westerling et al., 2006). How this translates into human impacts, such as property damages, will depend in part on how humans respond to wildfires through fire suppression, vegetation management, and decisions about where to build houses. Similarly, to understand how humans will be affected by vector-borne diseases, such as malaria, it is necessary to understand how their spread is driven by climatic and ecological factors (e.g. Ogden et al., 2014) as well as the steps that humans take to mitigate and avoid disease risks. In other words, accurate assessment of climate change risks must include a careful treatment of endogenous adaptation. A recent study on sea-level rise by Desmet et al. (2018) finds that ignoring endogenous adaptation results in estimates of global real GDP loss that are 40 times higher than with adaptation.

Risk is determined by three factors: hazard, exposure, and vulnerability. The hazard is the event that causes damages (e.g., a 2-meter rise in the sea level), exposure is the assets that could potentially be affected by the hazard (e.g., the value of real estate in low-lying areas), and vulnerability is the likelihood that the assets will be damaged. Economic studies of endogenous adaptation have focused on how humans are likely to reduce exposure and vulnerability in response to increased risk from climate change. For example, Desmet et al. (2018) and Balboni (2017) study how human migration and changes in production and trade patterns can reduce exposure to sea-level rise. Hinkel et al. (2014) provide global estimates of damages from sea-level rise that incorporate endogenous demand for infrastructure that reduces vulnerability. Analyses of heat-related mortality have emphasized how air conditioning reduces exposure to high temperatures (e.g. Barreca et al., 2016). Studies of the agricultural sector (e.g. Mendelsohn, Nordhaus, & Shaw, 1994; Burke & Emerick, 2016) have typically measured *implicit* adaptation, the response of outcomes like farmland prices or crop yields to differences or changes in climate. Studies of *explicit* adaptation in agriculture have focused on strategies that reduce exposure (e.g., changes in planting dates) or vulnerability (e.g., irrigation, crop switching, and use of new seed varieties) to extreme weather (Carter et al., 2018).

In this paper, we study fire suppression as an adaptive response to wildfire risk. This is an important topic of inquiry for three reasons. First, unlike in the examples discussed above, fire suppression reduces and ultimately eliminates the hazard itself (Baylis & Boomhower, 2019).[1] Although hazard reduction is the focus of mitigation studies (e.g., carbon taxes to limit warming), this margin has not been examined in the climate change literature on adaptation.[2] Second, predictions of future wildfire risks have emphasized biophysical factors (weather, fuel volume and moisture contents, etc.), and given little attention to the potential for adaptive human responses (Syphard et al., 2019). For example, Mann et al. (2016) and Syphard et al. (2019) model the effects of housing density, road networks, and proximity to population centers on wildfire characteristics

[1]Wildfire risk can also be mitigated through reductions in exposure (e.g., building houses in low fire-risk locations) and vulnerability (e.g., managing vegetation near buildings).

[2]Vector control through spraying of insecticides is another case of direct hazard reduction. Numerous studies predict how vector-borne diseases (malaria, dengue fever, West Nile virus, Lyme disease) will spread under climate change (Bouzid et al., 2014; Harrigan et al., 2014; Simon et al., 2014; Ryan et al., 2019), focusing on factors such as temperature, precipitation, and landscape features. None of these studies account for endogenous adaptation to increased disease risk.

and impacts (e.g., fire sizes, structure losses). However, these studies do not distinguish whether these factors indicate an adaptive response to wildfire risk, or are just correlates of exposure or vulnerability.[3] Finally, evidence that climate change is increasing wildfire activity in the western U.S. (Westerling et al., 2006), together with the recent, devastating fires in California, heightens the need to understand mechanisms for reducing wildfire risk.

Wildfire is an exceedingly complex spatial and dynamic phenomenon. This paper is a first step towards understanding how humans adapt to wildfire risk by allocating suppression effort. We combine a bio-physical model of potential wildfire spread with data on actual ignition points and burn scars to identify the determinants of the final extent of a given fire's burn area. Our analysis emphasizes the behavioral response of suppression activities to the nature of the housing stock lying in a fire's path, which is indicative of a fire's potential cost. Our study highlights the role of hazard reduction in determining the eventual scale and scope of climate change impacts—with a long-run goal of imbedding such response pathways in integrated modeling exercises that will inform future policy-making.

Focusing our analysis on the western U.S., we explicitly model the relationship between the built environment and fire spread in a manner that allows us to infer how fire managers allocate resources to protect housing assets and human populations within individual wildfire incidents. In a departure from the reduced-form wildfire studies referenced above, we make use of a fire simulation model developed by the U.S. Forest Service and used in the management of actual wildfire incidents. The fire simulation model, known as Minimum Travel Time (MTT), integrates spatial data as well as time-varying vegetation and winds data to predict wildfire behavior on the landscape in absence

[3]For example, more houses in an area could reduce structure loss by inducing more fire suppression effort, but increase it by raising the exposure of properties to wildfire risk.

of suppression. We then estimate a spatial-dynamic model of fire spread and suppression using the observed spatial distribution of human assets and landscape characteristics, which determine suppression benefits and costs, as a proxy for unobserved suppression effort. Importantly, assets at risk may be spatially-correlated with other physical factors that affect fire spread (e.g. fuels and topography). A critical feature of our approach is our use of predictions from the MTT model to holistically condition on physical determinants of wildfire spread. Contrasting fire spread across locations where wildfire behavior is similar but assets at risk are different allows us to attribute the effects of assets at risk on fire spread to suppression effort on behalf of those assets.

We find that the probability that a fire ceases its spread increases as fire approaches assets of concern to fire managers, even after controlling for variation in simulated fire behavior. We find that, ceteris paribus, increasing either the number, average value, or total value of houses at a given location within a fire's potential path markedly decreases the probability that the fire burns through said location. These differences almost certainly reflect the impact of fire suppression activities and are likely to have meaningful effect on the overall costs of structure loss due to climate-driven increases in wildfire.

The paper will proceed as follows. In the next section, we will provide some background on wildfires and wildfire management within the western U.S. We then develop a simple model of wildfire management. This model is useful for motivating the empirical spatial duration model used in the econometric analysis. It also provides qualitative predictions regarding the factors that should affect allocation of suppression effort. In section 4, we describe the econometric spatial duration model. We describe the data, including data derived from USFS fire simulation models, in section 5. We then present results, and conclude with a discussion of implications of the results for wildfire management and models of impacts due to climate change.

2 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 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 land owners and land management agencies. On unincorporated private lands, landowners generally yield responsibility for fire suppression to state agencies (eg. CalFire). Federal and state land management agencies are responsible for managing fires that burn on their lands, but they frequently share resources in order 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 a set of 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 on every incident. Even where national forests or other local units have developed local fire policies or plans, wildfire incidents will vary in firefighting resources available, weather conditions, and specific assets threatened. The emergency nature of wildfires requires that fire managers be allowed a high degree of discretion to make strategic decisions to minimize losses.

Fire suppression proceeds in two phases. Upon initially discovering a fire, the nearest fire management authority will usually attempt to quickly extinguish it in what is known as the "initial attack."[4] When fires escape managers' initial attempts at containment, fire suppression enters extended attack. During extended attack, fire managers rely on three sets of tactics: direct attack, aerial attack, and indirect attack (NWCG, 2017). Direct attack includes tactics in which firefighters directly apply treatment to burning fuel. Direct attack tactics are typically used when fires are relatively small, which enables firefighters to work close to burning material and physically smother the flames, or apply water or chemical retardant. Aerial attack involves applying water or chemical fire retardants from the air using helicopters or fixed-wing aircraft. Finally, 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 in order to stop a fire's spread. Fuel breaks can be constructed using hand tools or heavy equipment, or by "backburning", which involves taking advantage of favorable wind conditions and setting fire to fuels in the main fire's path, thus creating a fuel break. Fire managers can also take advantage of pre-existing fuel breaks, such as roads.

In choosing how to deploy suppression resources, fire managers face a set of loosely-defined incentives. Managers do not own the assets they are charged with protecting. Therefore, their decision-making is subject to a variety of 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 stategic 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 & Brown, 2005; Taylor,

[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 ignitions, regardless of the specific jurisdiction on which it occurs.

2019). While incentives facing fire managers are poorly defined, we follow much of the fire management literature in assuming that fire managers simply choose strategies to minimize the sum of suppression costs and wildfire damages (Sparhawk, 1925; Donovan & Rideout, 2003). Importantly though, we allow weights to be determined empirically, and avoid making assumptions about how bureaucratic incentives bear on the relative importance managers give to costs and protection of various assets.

Finally, the decision-problem 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 foward-looking over space and time, anticipating where 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 a series of sophisticated wildfire simulation software tools, 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 the empirical model, we use fire simulation models to help control for effects of spatial variation in fuels and topography on wildfire spread.

3 Theory

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

To begin, we allow to fire spread in multiple discrete directions, indexed by ℓ, from its ignition point. In order to avoid tracing fire spread across both distance and time, we assume the fire burns at unit speed in all directions. Therefore, at time $t = s$, the fire is distance s from its ignition point in each direction ℓ, conditional on it not yet having been extinguished in that direction. Values-at-risk in location $s\ell$ are described by the vector $\mathbf{x}_{s\ell}$. If the fire burns to distance s in direction ℓ, the fire destroys assets present at that location, and fire managers lose utility $u(\mathbf{x}_{s\ell})$. Ignitable fuels at distance s in direction ℓ are given by $r_{s\ell}$. At each location $s\ell$, the probability the fire is extinguished is a function of both fuels in that location and effort $e_{s\ell}$ expended toward suppressing the fire. Therefore, we write the probability the fire is extinguished at point s, conditional on reaching point s, as $\lambda(e_{s\ell}, r_{s\ell})$, and assume $\lambda(\cdot)$ is decreasing in fuels, and increasing in effort. Additionally, we assume that the marginal effect of effort on extinction probability is decreasing in fuels. The fire manager allocates effort across directions-of-spread ℓ in order to minimize expected losses across all directions. We define $\boldsymbol{y}_s$ as a $1 \times L$ vector of state variables, where L is the total number of directions over which the fire can spread. Each element $y_{s\ell}$ of $\boldsymbol{y}_s$ is a binary variable equal to zero if the fire has not yet been extinguished in direction ℓ at distance s. Therefore, the law of motion for each element of $\boldsymbol{y}_s$ is:

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

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

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

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

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

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

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

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

4 Empirical model

4.1 Fire spread distance as duration

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

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

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

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

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

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

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

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

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

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

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

4.2 Specification of spread-distance model

In order to estimate equation 7, we assume extinction probability is of the form:

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

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

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

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

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

A variety of physical variables—including topography, forest conditions, fuel moisture, wind, and temperature—can interact in complex ways to affect fire spread. In order to account for the

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

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

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

4.3 Identification & inference

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

As indicated above, the assumption that extinction probabilities are independent across directions of spread is likely false. Derivation of equation 7 requires the independence assumption, therefore violations of independence may bias 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 to marginal effects from equation 10. Since the LPM does not rely on the independence assumption for unbiasedness, this comparison provides a check for possible bias in marginal effects estimated from equation 10. As a second test, we vary the number of directions of spread L within each fire and test how results depend on how finely spread directions are partitioned, since correlation among spread directions should decrease as the number of directions of spread within each fire is reduced. Finally, we include fire-specific fixed effects in our preferred specification of equation 9. Fixed effects account for a specific form of non-independence in probability of extinction across fires—when fixed differences exist 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 & Miller, 2010).

5 Data

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

5.1 Wildfire data

Data describing areas burned come from the Monitoring Trends in Burn Severity (MTBS) project (MTBS, 2014). Since 1984, the MTBS has used Landsat satellite imagery to map the geographic extent of all fires greater than 1000-acres in size in the western U.S. Therefore, estimated effects of suppression and variation in suppression effort across groups should be interpreted as representing suppression within the subset of fires that escape initial containment and grow to be relatively large. It is possible that suppression on these incidents differs from suppression on the broader set of wildfire ignitions, which would cause selection bias. For example, fires may fail to reach the 1000-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 proxying for effort using the spatial distribution of assets-at-risk. The latter has potential to bias estimates of suppression effectiveness, but would tend to bias estimates toward zero.

Ignition locations are from the Fire Program Analysis Fire Occurrence Database (Short, 2017), which provides a comprehensive database of wildfires within the U.S. from 1993-2015 using a variety of federal, state, and local sources. Fires within the database include coordinates of each fire's point of origin accurate to within 1 km. The database includes even small ignitions that never grew to be threatening fires. In addition to restricting our attention to the set of fires that grew large enough to be mapped by MTBS, we focus on fires in the western U.S. in years 1999-2015 whose ignitions were within 10 km of the wildland urban interface.[6] We focus specifically on the western

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

U.S. because wildfire hazard is a significant concern in the region, and because fire regimes in the western U.S. are distinct from those in the east. The sample of fires is restricted to fires beginning within 10 km of wildland urban interface for two reasons. First, due to concern over protection of private property, fires that begin within 10 km of wildland urban interface are likely to induce the most forceful suppression responses. Indeed, some fires that begin in very remote areas are not suppressed, and are instead managed to provide ecological benefits. Second, one of our interests is differences in suppression on behalf of varied communities. This set of fires includes only fires that directly threaten at least some human communities. Finally, we exclude from the sample all "complex" fires, large incidents in which multiple ignitions are jointly managed due to their close proximity to one another.

The remaining 1,503 fire ignitions, locations of which are shown by markers in Figure 1, comprise the full sample of fires analyzed in regression models that make use of Census data to measure assets at risk. As described further below, we also explore measuring assets at risk using assessors' data on housing locations and values.

To adapt the empirical model from the previous section to the data, we divide the area surrounding each wildfire ignition point into L directions of spread. Figure 2 provides an example. In the primary set of results, L equals 24 and each direction of spread has a central angle of 15 degrees, though we check robustness of our results to varying values of L. We further divide each direction of spread into a series of 1 km distance intervals, up to a maximum distance (M) of 20 km, creating a circular grid surrounding each ignition location. We overlay the circular grid with the corresponding wildfire perimeter and code the fire as being extinguished ($y_{m\ell} = 1$) within a cell if fire fails to reach cell's centroid.[7] We code all prior cells (those nearer to the ignition point)

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

within the direction of spread as burnt ($y_{m\ell} = 0$). We refer to the distance interval at which the fire is first extinguished within each direction as interval M_ℓ, and we drop all observations within each direction ℓ for which $m > M_\ell$. Fires sometimes spread in irregular non-convex patterns, and they may return to a direction of spread from which they have previously been extinguished. We treat fires as remaining extinguished once they have first been extinguished within a direction of spread.[8] Figure 4 shows the distribution of fire spread distances. For almost 90% of spread-directions, fires are extinguished within 5 km of the ignition point. Fewer than 0.5% of spread-directions are right-censored by the maximum distance of 20 km, implying that estimates are unlikely to be biased due to omission of burnt areas beyond the maximum distance.

5.2 Determinants of fire suppression effort

Fire suppression effort is a function of at-risk assets within a given direction of spread, and of costs of suppression. To account for variation in suppression effort on behalf of populations at risk, we use a combination of U.S. Census data, collected at the block and tract-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 to 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 some 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 many other demographic variables, including race, are available only at the Census tract-level. To map Census block and tract-level data to the circular grids surrounding each ignition point, we assume

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

that populations are uniformly distributed within each Census block, and that Census blocks are demographically uniform within each tract. Given the large area of many Census tracts in rural parts of the western U.S. and the uneven nature of housing distributions across these large tracts, this approach may result in significant measurement error for tract-level income variables.

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

As is clear from Figure 2, circular grid cells vary in area. The increase in affected area as fire spreads away from its point of origin captures a natural feature of spatial dynamic phenomena; spread may be more damaging, and more costly to control, as it proceeds and the perimeter of the affected area expands (Epanchin-Niell & Wilen, 2012). Consistent with this feature of fire spread, we use area-dependent measures to capture both benefits and costs of controlling fire within a grid cell. Within models using Census data, we proxy for the number of homes in a cell using the total number of housing units. As a proxy for the total value of homes within each cell, we use total housing units multiplied by per-capita income, which we refer to as "total income."[11] To allow that

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

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

[11]In theory, the number of housing units an area could affect both benefits of suppression and costs of suppression, if suppression costs vary by housing density. We expect differences in effects of density on fire spread will be captured by our fire simulation model outputs, which will be described in the following subsection. Nevertheless, because our

fire managers may undertake greater suppression effort on behalf of higher income residents, we also include per capita income. While not central to our analysis, it would be of potential interest to explore differences in suppression effort by race or by other demographic characteristics. However, due to a lack of variation in Census race variables, we focus on differences in effort by income and property value.[12]

For models using assessors' data, we use measure analogous variables for each grid cell: 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 cell are 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 assessor's data models we use residential property values and consider them to be a proxy for residential structure values.

In its first panel, Table 1 summarizes demographic characteristics by distance from ignition point. There is a clear trend in population density (as well as total income) over distance from the ignition point. This is likely due to selection; a fire is more likely to grow to be large, and therefore to be included in the sample, if it begins in a more rural location. This suggests that, in estimating the effect of population on extinction probability, controlling for distance from ignition may be important to account for secular trends in demographic characteristics as well as to control for effects of duration dependence. Though protection of private property is a primary

specification includes distance from ignition effects, which in our model control for the area of each circular grid cell, including the number of homes rather than housing density has a minor effect on results.

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

concern of fire managers, they may also be concerned with protecting a variety of other assets, including watersheds and threatened and endangered species habitat. We collected data describing the spatial distribution of these assets,[13] however they did not have statistically significant effects on suppression effort, and so they are not included in the models presented here.

To account for differences in the cost of fire suppression over space, we collected data on accessibility and topographic ruggedness. We measured costs associated with ruggedness by calculating topographic ruggedness index (TRI), which measures the variation in elevation among a pixel and its neighbors (Riley, 1999; Nunn & Puga, 2012), at the 30 m pixel level across the landscape surrounding each ignition point. We then averaged TRI within each circular grid cell and multiplied average TRI by cell area to capture increases in costs due to expansion of the affected area. We measured accessibility as the total area within each cell that is within 0.5 km of a road. Another important factor affecting cost of effort is the availability of personnel and equipment resources. Fire-fighting resources shared across federal and state agencies are dispatched by a network of command centers according to need and availability (Bayham & Yoder, 2020). Among the models estimated in the next section are models including fire-level fixed effects. National demand for and availability of fire-fighting resources varies over time but is likely relatively constant over the course of a wildfire incident. Therefore, fire-level fixed effects should account for differences across fires in availability of resources. In its second and third panels, Table 1 summarizes how cost varies with distance from the ignition point. To better illustrate trends in distance from the ignition point, the table includes per area measures of these variables.

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

5.3 Physical fire spread variables

Finally, we control for natural factors affecting fire spread through inclusion of outputs from a model of fire spread. The USFS has developed various fire simulation software (including Farsite, Flammap, and FSPro), which differ in their applications within fire 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 within wildfire incidents to assess uncertainty and aide 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 accurate models of fire behavior with relatively low computational cost (Finney, 2002), making it ideal for retrospective simulation of thousands of historical wildfires. MTT takes as inputs features of the landscape such as elevation, slope, and aspect, and characteristics of vegetation on the landscape. As well, it requires the user to specify initial fuel conditions; fuel moistures then evolve over the course of the fire simulation. Topographic data and time-varying vegetation and fuels data come from the Landfire project (Landfire, 2014), which provides remotely-sensed landscape data at a 30 m resolution.[14] Finally, MTT simulations take into account weather and wind values. We collected observed wind speed and wind direction at the time of each ignition from its nearest Remote Automated Weather Station (RAWS station).[15]

[14]Vegetation characteristics comprise 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 years 2000-2005, 2008 data for years 2006-2010, and 2010, 2012, and 2014 data for the two years following each of those updates.

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

Fire simulation models such as MTT perform well in predicting fire behavior and patterns of fire perimeter expansion across the landsape, but they are not designed to predict the final extent of a fire's spread—final fire perimeters output 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 kilometers of its ignition point. Forcing the 20-km circular grid to be entirely consumed by fire generates a series of landscape-wide measures describing how fire would be expected to burn within a 30 m pixel, conditional on fire having reached that pixel. Among these measures are landscape-wide surfaces of fire intensity and fire arrival time. Fire intensity measures heat generation per unit time within a pixel, while fire arrival time measures the time since fire ignition at which a fire is expected to reach a given 30 m pixel. We measure arrival time within circular grid cell $m\ell$, which we denote $T_{m\ell}$, as the time at which fire is expected to reach the centroid of cell. Previous studies have used fire rate of spread as a predictor for fire extinction (Peterson et al., 2009), and it is reasonable to expect that fire will be more likely to stop spreading where it travels more slowly. Therefore, we calculate $\Delta T_{m\ell} = T_{m\ell} - T_{m-1,\ell}$,[16] and use this discretized rate of spread between cells as our primarily predictor of the effects of physical factors on probability of fire extinction.[17] We simulated fire spread for each of the 1,503 wildfires in the sample. An example of how MTT outputs are used is provided in figure 3. Panel A illustrates the surface of simulated arrival times across the landscape surrounding an example fire ignition. Panel B illustrates the outcome of averaging arrival times within cells, and taking differences across successive cells.

MTT does not simulate fire spread within areas without fuels (eg. highly urbanized areas or

purposes

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

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

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

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

where $\ln(\Delta T_{m\ell} + 1)$, and $\ln(Intensity_{m\ell} + 1)$ is coded as 0 if fuel is absent in cell $m\ell$. The final panel of Table 1 describes how $Intensity$, T, ΔT, and the fraction of cells without fuels vary with distance from the fire ignition point. As one would expect, arrival time T is increasing with distance from ignition point. Rate of spread decreases with distance from ignition point, while the number of cells in which fuels are absent increases with distance, suggesting areas farther from a fire's site of origin are less likely to be favorable for fire growth.

6 Results

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

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

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

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

Table 3 presents parallel results to Table 2 using Census data and the full set of 1,503 wildfires.

Using Census data, we sacrifice some accuracy within our measures of housing and property values for a substantially increased sample size. Census data allows us to make use of fires across all western U.S. counties dating back to 1999. Results based on Census data are qualitatively similar to results based on assessors' data. Fires are more likely to go out within cells that contain greater numbers of homes, especially if per capita income within the cell is greater. Table 3 indicates that an increase in per capita income of $10,000 is associated with a 1 percentage point increase in the probability fire stops spreading within the cell.

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

As in Table 2, columns 5-7 indicate results are not sensitive to the choice of extinction probability functional form, or to the assumption of independence among fire spread directions. To provide a further test of independence among fire spread directions, Table 4 shows results from regressions specified as in column 4 of Tables 2 and 3, but estimated using data constructed with alternative numbers of fire spread directions around each ignition. From column 1 to 3 and from column 4 to 6, fire spread directions become more expansive, and the number of observations per fire declines.

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

Nonetheless, results are broadly similar across the columns. As would be expected, estimates attenuate and standard errors increase as the number of fire spread directions declines, but even in columns with just six directions of spread, some coefficients are statistically significant. This table indicate that the assumption of independence discrete directions of spread is not driving results.

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

Figures 5a and 5b illustrate distributed lead weights from models based on, respectively, as-

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

sessors' data and the limited 2012-2015 fire sample, and Census data and the full sample of fires. The Almon weighting specification assumes that spatial weights follow a quadratic function. Both specifications assume weights fall to zero by 6 km from the fire's current location. Coefficient estimates for each model are presented in the appendix in Tables A1-A4. As expected, weights generally decline with distance from the focal cell, falling to zero at approximately 3 km distance. Results are fairly similar across specifications using unrestricted and Almon weights, though the tendency for weights to "bounce" up and down is reduced by the use of Almon weights. Similarly to previous results, fires are more likely to stop spreading as they approach cells with residential properties, cells with more homes and cells where those homes are worth more (or where per capita income is greater). A possible concern facing results presented in Tables 2 and 3 is that fire simulation variables do not adequately control for the effects of fuels on fire spread, and so results reflect the direct effect of homes on fire spread via fuels rather than effects due to increased suppression effort. Results in Figure 5 provide evidence of spatially forward-looking behavior in fire management, and provide confidence that suppression effort on behalf of homes is driving results; residential properties 2-3 km away from a fire's current location can effect fire spread through their effect on suppression effort but not through direct effects via fuels.

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

7 Conclusion

Understanding and predicting climate-driven changes in risk is critical for many sectors of the economy. Much work has been done to model the natural systems that underpin this risk. Markedly less work has been done to understand and model human behavioral responses to environmental risk and how these responses then feed back into the natural system to alter climate-driven changes in risk to life, property and health. Endogenous adaptation is likely to play a central role in shaping many natural hazards under climate change: growth in wildfire occurrence and severity; increases in heat-related mortality; the spread of vector- and water-borne diseases; and heightened risks from coastal and inland flooding. In this paper, we develop methods to include endogenous adaptation in natural hazard risk analysis. Specifically, we synthesize a bio-physical model of wildfire spread with an econometric assessment of fire extinction/suppression to identify the ways in which behavioral responses to the built and natural environment modify the risk of fire spread relative to the baseline bio-physical model.

The results of our analysis suggest that human interventions in the form of fire suppression activities are significantly altering the spatial distribution of wildfire risk relative to a no-intervention baseline. We identify how fire extinction probabilities change as wildfire approaches an area of human habitation. Controlling for a broad set of covariates including fire behavior characteristics derived from a fire simulation model allows us to attribute differences in extinction probability across space to differences in human-driven suppression activities on behalf of threatened assets.

In addition to fire suppression activities by public agencies, a variety of factors determine whether a home is destroyed in a wildfire. Building materials, home maintenance, and landscaping can substantially influence the likelihood a fire is destroyed in a wildfire (Cohen, 2000; Syphard, Brennan, & Keeley, 2014). As well, owners of very high value of homes may have access to private firefighting services, such as through their insurance policy (Varian, 2019). While these factors can be important determinants of home loss, they are likely to have a limited influence on the outcome variable used in this study, the overall area burnt in wildfires. A related threat to identification would occur if effects of local fire hazard reduction on fire spread in areas with more homes or higher value homes were not fully captured by our fire simulation outputs. The pattern observed in spatial lead coefficients, however, suggests that spatially forward-looking suppression effort undertaken by fire management agencies is indeed driving our results.

While the baseline probability of suppression at a given point along an average fire's path through undeveloped terrain is roughly 38%, we find that fire spread is 5.9 percentage points more likely to be halted when a fire is approaching a typical (in terms of number and values of properties) inhabited area. Increase the average value of properties in the fire's path from $200,000 (average) to $400,000 and the probability of suppression increases another 2.7 percentage points. This second estimate implies that doubling the average value of the homes in a fire's path (holding the number of homes constant) yields a suppression response that is roughly half the magnitude of the baseline response to placing homes in the fire's path to begin with. While not the focus of our work, this result provides a new wrinkle to the literature on environmental justice which has shown that minority and low-income households are disproportionately exposed to environmental harm (Banzhaf, Ma, & Timmins, 2019b,a; Mohai, Pellow, & Roberts, 2009). 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%.

To simplify our spatial-dynamic analysis, this paper assumed fires spread linearly from their ignition points. While we believe this simplification is justified, it may lead us to mismeasure anticipated directions of fire spread, thus attenuating our estimates of the effect of suppression activity on fire spread. Nonetheless, given that annual costs of structure loss to wildfires were estimated to be on the order of $600 million in 2016, the economic impact of even a 20% difference in probabilty of suppression is likely to be non-trivial.

While this work is only an initial foray into the process of incorporating human behavior into biophysical models, our estimates clearly demonstrate that a failure to account for the human element in modeling fire spread could lead to a marked mischaracterization of risk patterns associated with an increase in fire activity. Further, our modeling demonstrates that, at least in some cases, incorporating such behavioral elements into biophysical models is potentially straightforward. It is impossible to extrapolate directly from this analysis to other contexts and processes. However, our expectation is that as researchers further explore these issues that this scale of import will likely come to be seen more as the norm than the exception.

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

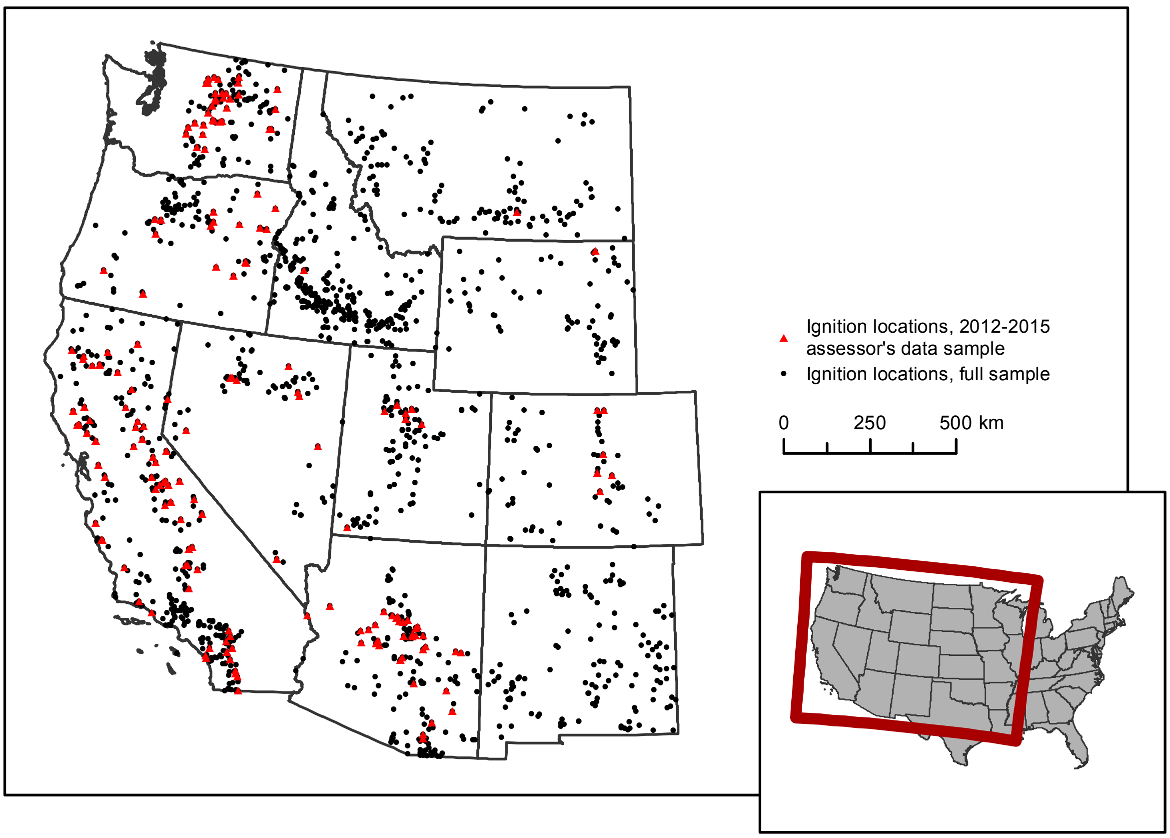


Figure 2: Illustration describing the construction of the data set. The landscape surrounding each ignitition point is divided into 24 discrete directions of spread. Each direction of spread is divided into 1-km distance intervals, up to a maximum distance of 20 kilometers, yielding a circular grid surrounding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

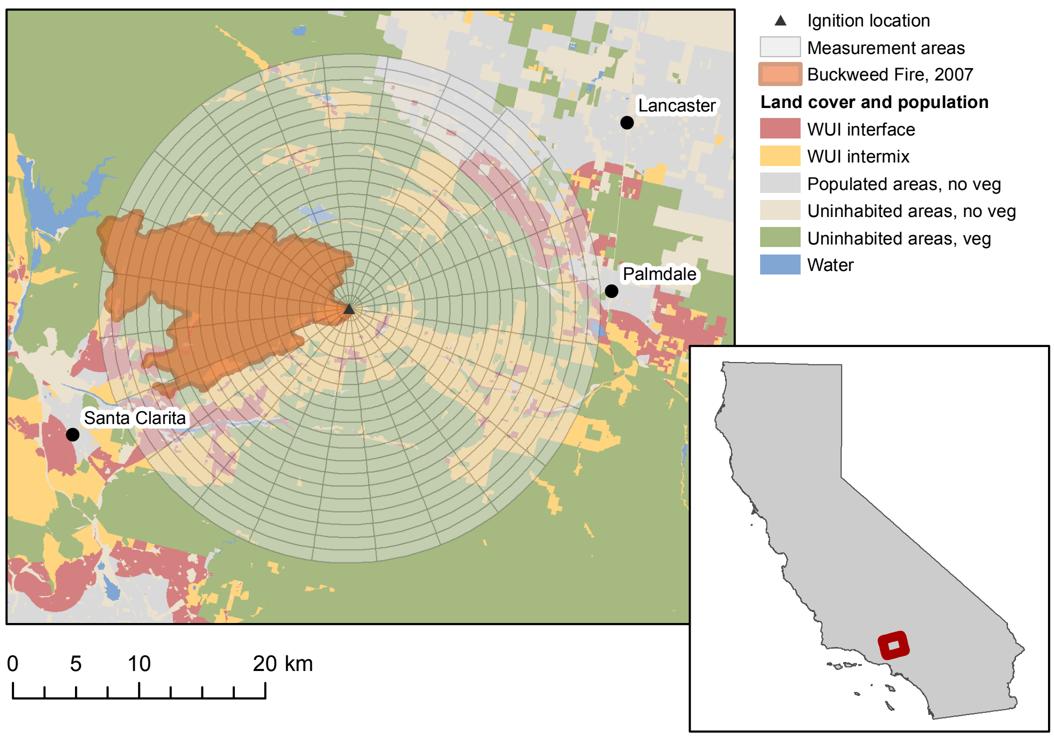


Figure 3: Illustration of fire simulation output

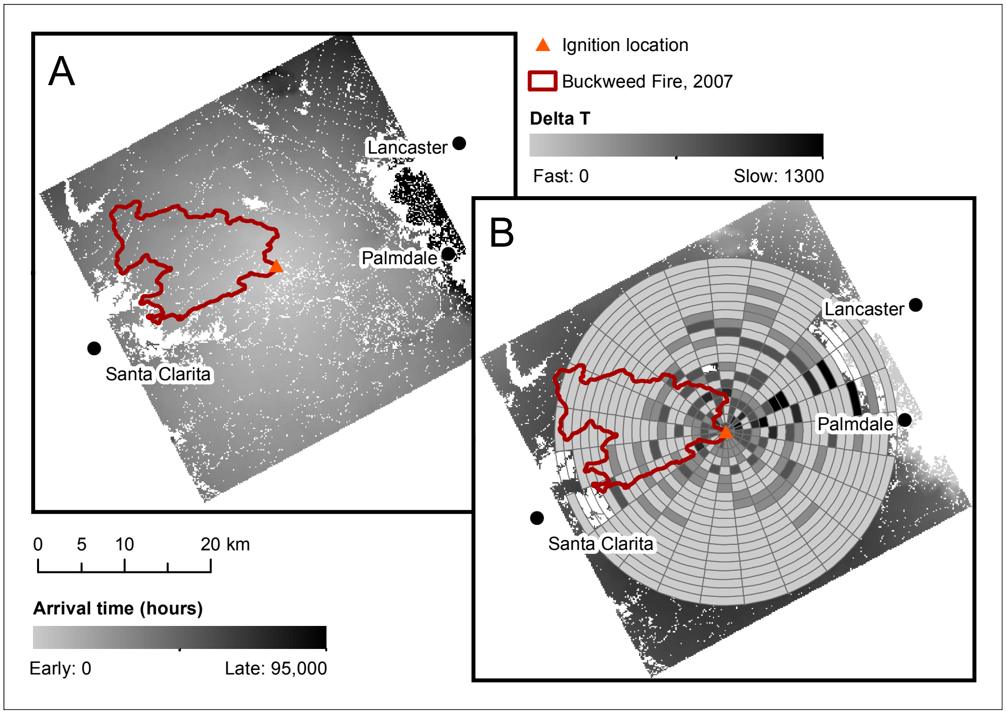


Figure 4: Histogram of fire spread distances. Fire is extinguished within 5 km of the ignition point for nearly 90% of spread directions. Fires burn beyond the maximum observed distance of 20 kilometers in fewer than 0.5% of spread directions.

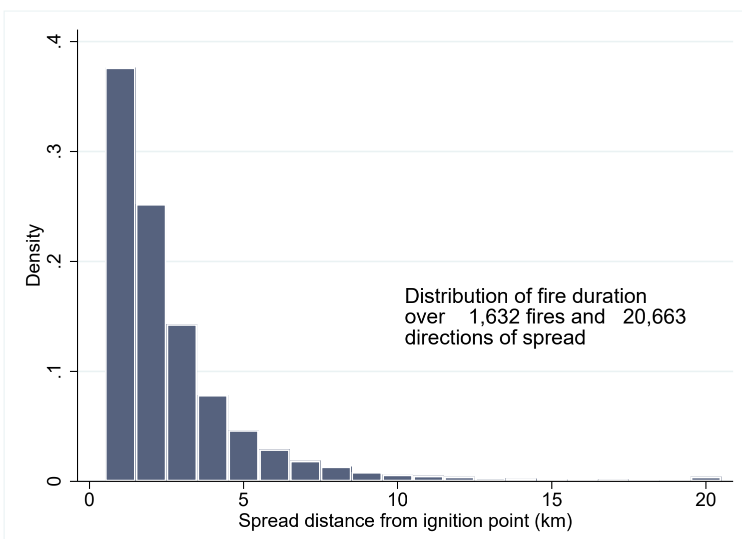
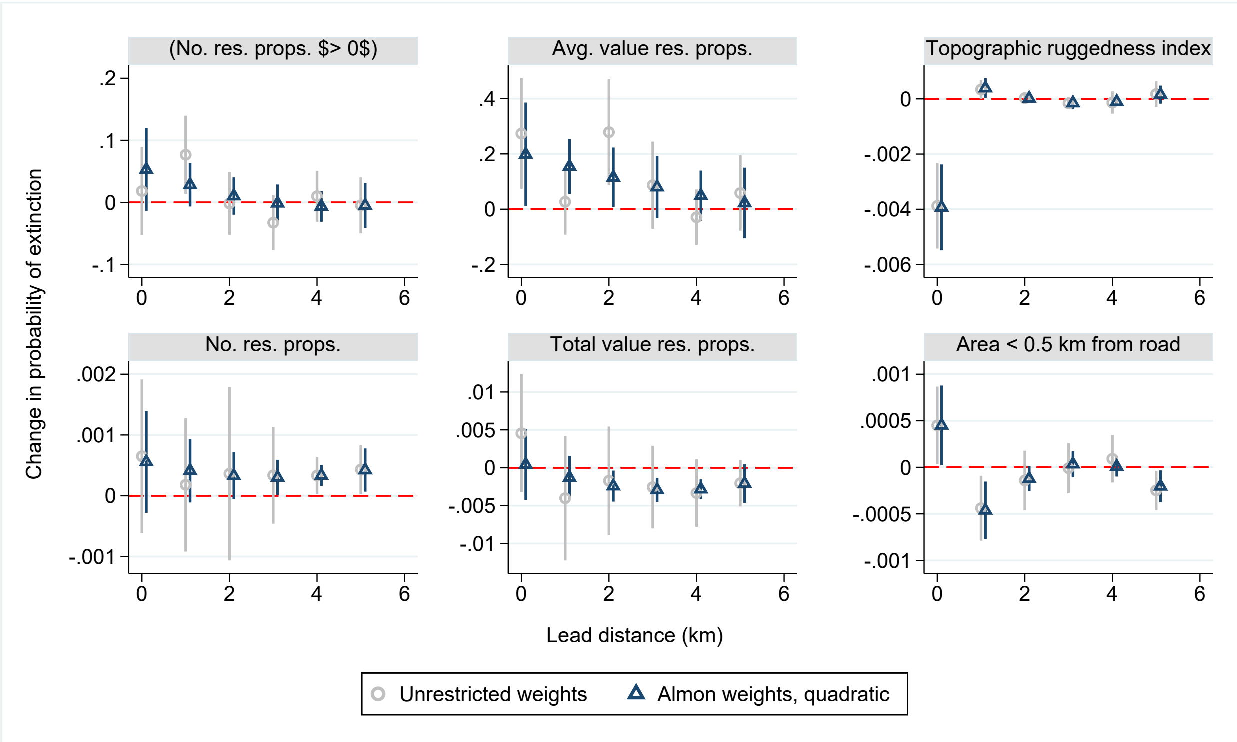
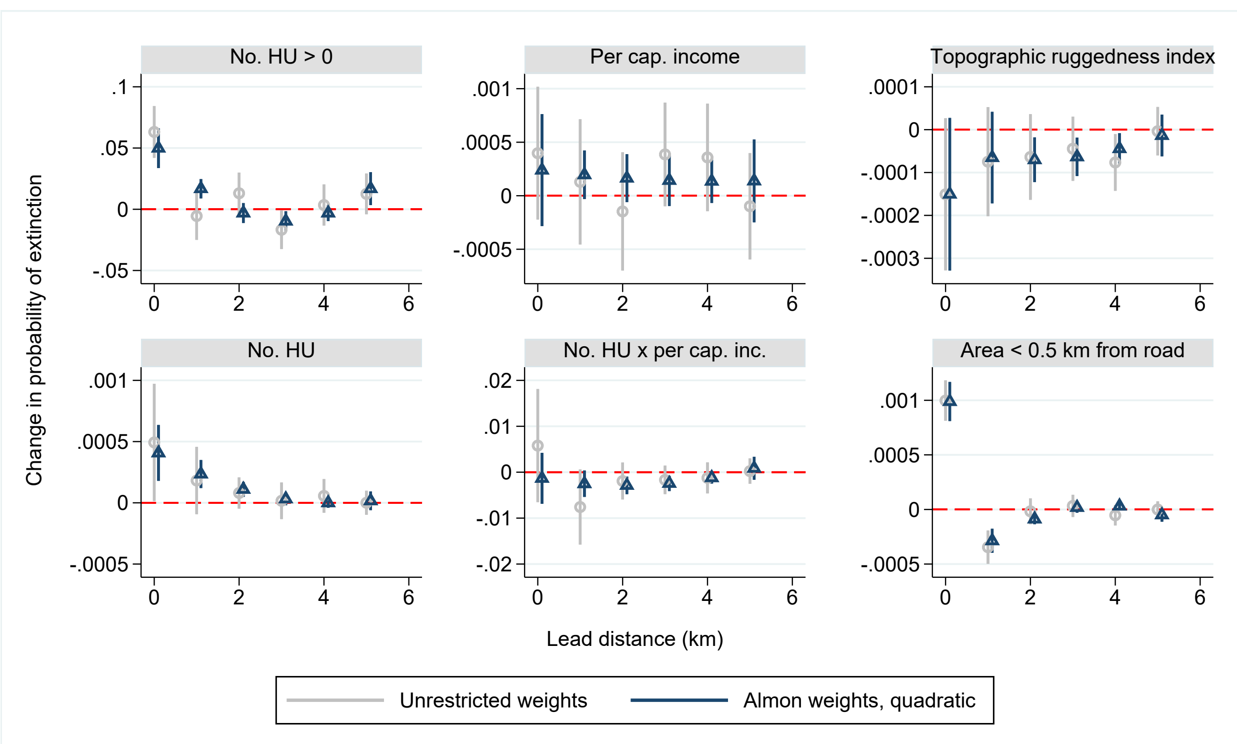


Figure 5: Weights estimated from distributed spatial lead models using housing variables from Census data and California assessor's data.



(a) Assessors' data



(b) Census data

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

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

Table 2: Results from regressions using assessors' data. Spatial leads are omitted.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(No. res. props. > 0)	.071		.0051	.045	.054	.058	.049
	[.043]		[.031]	[.039]	[.041]	[.039]	[.036]
No. res. props.	.0014		.00092	.0012	.0011	.0012	.0014
	[.00051]		[.00069]	[.00046]	[.00066]	[.00064]	[.00063]
Avg. value res. props. (millions USD)	.23		.28	.26	.27	.27	.31
	[.11]		[.092]	[.1]	[.11]	[.11]	[.098]
Total value res. props. (millions USD)	-.0041		-.001	-.0039	-.0032	-.0037	-.0046
	[.0038]		[.0034]	[.0027]	[.0042]	[.0036]	[.0032]
Topographic ruggedness index	-.0041		-.0082	-.0052	-.0046	-.004	-.0031
	[.001]		[.001]	[.00097]	[.00087]	[.00075]	[.00069]
Pct. < 0.5 km from road	.00056		-.000018	.00024	.0002	.00016	.00011
	[.00025]		[.00024]	[.00024]	[.00022]	[.00021]	[.00016]
Ln($\Delta T1$)		.1	.045	.1	.092	.09	.091
		[.017]	[.014]	[.017]	[.016]	[.016]	[.016]
Ln(Intensity)		.096	.058	.1	.095	.092	.095
		[.02]	[.012]	[.02]	[.018]	[.018]	[.019]
Contains major road		.19	.19	.18	.19	.19	.19
		[.032]	[.031]	[.032]	[.036]	[.035]	[.037]
ΔT missing		.37	.22	.36	.36	.35	.35
		[.046]	[.039]	[.046]	[.046]	[.045]	[.047]
Specification	Comp. log-log	Comp. log-log	Comp. log-log	Comp. log-log	Logit	Probit	LPM
Fire fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
Number obs.	11,096	11,096	11,096	11,096	11,096	11,096	11,096
Number fires	179	179	179	179	179	179	179

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

Table 3: Results from regressions using Census data. Spatial leads are omitted.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(No. HU > 0)	.079		.025	.065	.065	.065	.065
	[.012]		[.0099]	[.011]	[.01]	[.01]	[.0097]
No. HU	.00096		.00071	.00078	.0013	.001	.00059
	[.00036]		[.0002]	[.00037]	[.00044]	[.00039]	[.00024]
Per cap. income	.0012		.00076	.00074	.00062	.00061	.00059
	[.00037]		[.00029]	[.00033]	[.00033]	[.00033]	[.00029]
No. HU x per cap. inc.	-.0062		-.0067	-.0048	-.0085	-.0073	-.0015
	[.0075]		[.0046]	[.0076]	[.0078]	[.0073]	[.005]
Topographic ruggedness index	-.000016		-.00096	-.00012	-.00012	-.00011	-.000053
	[.000069]		[.00068]	[.00011]	[.0001]	[.000076]	[.000036]
Pct. < 0.5 km from road	.0012		.0011	.00094	.00086	.0008	.00067
	[.0001]		[.00012]	[.000093]	[.000087]	[.000083]	[.000074]
Ln($\Delta T1$)		.13	.079	.13	.12	.12	.12
		[.0063]	[.0057]	[.0062]	[.0062]	[.006]	[.0061]
Ln(Intensity)		.11	.06	.11	.1	.1	.11
		[.0075]	[.0045]	[.0075]	[.007]	[.0065]	[.0069]
Contains major road		.18	.14	.14	.16	.16	.16
		[.013]	[.013]	[.013]	[.015]	[.014]	[.015]
ΔT missing		.5	.35	.48	.49	.49	.5
		[.016]	[.016]	[.016]	[.017]	[.016]	[.018]
Specification	Comp. log-log	Comp. log-log	Comp. log-log	Comp. log-log	Logit	Probit	LPM
Fire fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
Number obs.	88,568	88,568	88,568	88,568	88,568	88,568	88,568
Number fires	1,503	1,503	1,503	1,503	1,503	1,503	1,503

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

Table 4: Results from regressions using Census data. Spatial leads are omitted.

	Assessor's Data			Census Data		
	(1)	(2)	(3)	(4)	(5)	(6)
(No. res. props. > 0)	.053	.066	.049			
	[.043]	[.039]	[.049]			
No. res. props.	-.00059	.00018	.000073			
	[.00054]	[.00016]	[.00012]			
Avg. value res. props. (millions USD)	.25	-.017	.087			
	[.095]	[.076]	[.2]			
Total value res. props. (millions USD)	.0013	-.0014	.0045			
	[.0028]	[.00093]	[.0033]			
(No. HU > 0)				.071	.059	.068
				[.011]	[.013]	[.014]
No. HU				.0013	.00072	.00014
				[.00069]	[.00023]	[.000088]
Per cap. income				.00083	.00062	.00047
				[.00034]	[.00036]	[.00036]
No. HU x per cap. inc.				-.009	-.0084	.00071
				[.014]	[.0054]	[.0022]
Topographic ruggedness index	-.0083	-.0033	-.00094	-.00024	-.00017	-.00011
	[.0019]	[.00062]	[.00049]	[.00018]	[.00012]	[.000068]
Pct. < 0.5 km from road	.0016	.00039	.0002	.0018	.00058	.00024
	[.0004]	[.00017]	[.00014]	[.00016]	[.000067]	[.00005]
Ln($\Delta T1$)	.09	.084	.12	.11	.13	.14
	[.016]	[.02]	[.024]	[.006]	[.0067]	[.0083]
Ln(Intensity)	.058	.12	.16	.068	.15	.18
	[.015]	[.023]	[.032]	[.0059]	[.0089]	[.011]
Contains major road	.17	.14	.12	.15	.12	.11
	[.035]	[.035]	[.038]	[.014]	[.014]	[.016]
ΔT missing	.33	.35	.42	.41	.48	.53
	[.046]	[.058]	[.077]	[.016]	[.019]	[.024]
Fire fixed effects	48	12	6	48	12	6
Number obs.	Yes	Yes	Yes	Yes	Yes	Yes
Number fires	20,831	5,382	2,558	166,822	41,393	20,589
numfires	170	171	162	1,451	1,394	1,338

Note: Standard errors are in parentheses and are clustered by fire.

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. Results are calculated from a linear probability model with five spatial leads, restricted using quadratic Almon weights.

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

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

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

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

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

Table A2: Results from linear probability model estimated with 5 unrestricted distributed spatial leads for variables related to benefits and costs of fire suppression. Proxies for housing come from the US Census.

	Spatial leads					
Variable	m	$m+1$	$m+2$	$m+3$	$m+4$	$m+5$
(No. HU > 0)	.063	-.0055	.013	-.017	.0035	.013
	(.011)	(.0099)	(.0086)	(.008)	(.0086)	(.0085)
No. HU	.00049	.00018	.00008	.000017	.000056	4.5e-07
	(.00024)	(.00014)	(.000065)	(.000076)	(.00007)	(.00005)
Per capita income (thousands USD)	.0004	.00013	-.00015	.00039	.00036	-.000098
	(.00032)	(.0003)	(.00028)	(.00025)	(.00026)	(.00025)
No. HU x per cap. inc.	.0058	-.0076	-.0019	-.0017	-.0012	.00024
	(.0063)	(.0042)	(.002)	(.0016)	(.0017)	(.0014)
Topographic ruggedness index	-.00015	-.000075	-.000064	-.000044	-.000076	-3.5e-06
	(.00009)	(.000065)	(.000051)	(.000038)	(.000034)	(.000029)
Pct. < 0.5 km from road	.001	-.00035	-.000017	.000033	-.000053	-1.3e-07
	(.000094)	(.000078)	(.000061)	(.000052)	(.000048)	(.000038)
Ln(ΔT 1)	.12					
	(.0062)					
Ln(Intensity)	.11					
	(.0069)					
Contains major road	.16					
	(.015)					
ΔT missing	.51					
	(.018)					
Fire fixed effects	Yes					
Number obs.	86948					
Number fires	1499					

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

Table A3: Estimated weights for variables related to benefits and costs of fire suppression from a linear probability model estimated with 5 distributed spatial leads restricted using quadratic Almon weights. Housing variables are drawn from county assessors' data.

	Spatial leads					
Variable	m	$m+1$	$m+2$	$m+3$	$m+4$	$m+5$
(No. res. props. > 0)	.053	.028	.01	-.0013	-.0064	-.005
	(.034)	(.018)	(.015)	(.015)	(.013)	(.018)
No. res. props.	.00056	.00041	.00033	.0003	.00033	.00042
	(.00042)	(.00027)	(.0002)	(.00015)	(.000088)	(.00018)
Avg. value res. props.	.2	.15	.12	.08	.049	.022
	(.095)	(.051)	(.055)	(.057)	(.046)	(.065)
Total value res. props.	.00043	-.0013	-.0024	-.0029	-.0028	-.0021
	(.0024)	(.0014)	(.001)	(.0008)	(.00065)	(.0013)
Topographic ruggedness index	-.0039	.00039	.000015	-.00015	-.0001	.00015
	(.00079)	(.00018)	(.000085)	(.00011)	(.00005)	(.00017)
Pct. < 0.5% km from road	.00045	-.00046	-.00012	.000034	7.1e-06	-.0002
	(.00022)	(.00016)	(.000068)	(.00007)	(.000054)	(.000087)
Ln(Δ1)	.095					
	(.095)					
Ln(Intensity)	.096					
	(.096)					
Contains major road	.19					
	(.19)					
ΔT missing	.36					
	(.36)					
Fire fixed effects	Yes					
Number obs.	10861					
Number fires	178					

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

Table A4: Estimated weights for variables related to benefits and costs of fire suppression from a linear probability model estimated with 5 distributed spatial leads restricted using quadratic Almon weights. Proxies for housing come from the US Census.

	Spatial leads					
Variable	m	$m+1$	$m+2$	$m+3$	$m+4$	$m+5$
(No. HU > 0)	.05	.017	-.003	-.0097	-.003	.017
	(.0083)	(.004)	(.0041)	(.0041)	(.0034)	(.0069)
No. HU	.00041	.00024	.00011	.000032	5.8e-07	.000016
	(.00012)	(.000058)	(.000031)	(.000027)	(.000021)	(.000039)
Per cap. income	.00024	.0002	.00016	.00014	.00014	.00014
	(.00027)	(.00012)	(.00011)	(.00012)	(.0001)	(.0002)
No. HU × per cap. inc.	-.0013	-.0025	-.0029	-.0024	-.0012	.00085
	(.0028)	(.0015)	(.00097)	(.00085)	(.00065)	(.0013)
Topographic ruggedness index	-.00015	-.000065	-.00007	-.000063	-.000044	-.000013
	(.000091)	(.000054)	(.000027)	(.000023)	(.000018)	(.000025)
Pct. < 0.5% km from road	.00099	-.00029	-.000088	.000018	.000031	-.00005
	(.000091)	(.000056)	(.000024)	(.000024)	(.000019)	(.000032)
Ln(Δ1)	.12					
	(.12)					
Ln(Intensity)	.11					
	(.11)					
Contains major road	.16					
	(.16)					
ΔT missing	.5					
	(.5)					
Fire fixed effects	Yes					
Number obs.	86990					
Number fires	1499					

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