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Essays on the Economics and Politics of Wildfire Management

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Essays on the Economics and Politics of Wildfire Management

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by

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Essays on the Economics and Politics of Wildfire Management

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Hand, M.S., Wibbenmeyer, M., Calkin, D.E., and Thompson, M.P. 2015. Risk preferences, probability weighting, and strategy tradeoffs in wildfire management. *Risk Analysis* 35(10): 1976-1891.

Wibbenmeyer, M., Hand, M.S., Calkin, D.E., Venn, T.J., and Thompson, M.P. 2013. Risk preferences in strategic wildfire decision making: A choice experiment with U.S. wildfire managers. *Risk Analysis* 33(6): 1021-1037.

Calkin, D.E., Venn, T.J., Wibbenmeyer, M., and Thompson, M.P. 2012. Estimating wildland fire managers preferences toward competing strategic suppression objectives. *International Journal of Wildland Fire* 22(2): 212-222.

Abstract

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by

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In the past several decades, wildfires in the western U.S. have become more severe, frequent, and damaging. Federal and state governments bear substantial responsibility for managing these incidents. Yet we know little about how government environmental managers make decisions, whether in this context, or in the many other contexts in which government administrators play an important role. In this dissertation, I use the example of federal wildfire management to study decision-making among government environmental managers. In the first essay, I estimate avoided losses to structures due to wildfire suppression. Though preventing losses to structures is a primary goal of wildfire suppression, avoided losses to structures do not justify costs of suppression for many wildfires, especially those that begin in remote areas. In the second and third essays, my collaborators and I explore consequences of behavioral biases among communities affected by wildfire management. In the second essay, we show that, due to pressure individuals place on government administrators, behavioral biases can affect the decision-making of public land management agencies. In the empirical context of this study, government decisions over where to locate wildfire risk reduction projects, this can result in inefficient policy outcomes. The third and final essay uses behavioral bias-induced shocks to community demands for wildfire risk reduction projects to study differences in responsiveness among government administrators to demographically-varying communities. We find that government administrators are more responsive to communities in which a greater percentage of residents are white, educated, or young.

Contents

Chapter 1

Introduction

Over the past several decades, wildfires within the western U.S. have become increasingly frequent, severe, and damaging. While this trend owes its explanation to a number of factors (including climate change), an important contributing factor has been the legacy of fire suppression on public lands in the western U.S. In the West, 69% of forest land, and 49% of land overall, is publicly owned. Beginning in the early twentieth century, land management agencies—led by the U.S. Forest Service—adopted a policy of fire exclusion. In many western U.S. forest types, fire exclusion has led to an accumulation of fuels, increasing the risk that ignitions develop into severe and hazardous wildfires. Because of the federal government's role in contributing to current conditions in western forests, advocates for divestiture of public lands have cited the example of wildfire to argue that the federal government is ill-prepared to manage its extensive landholdings (e.g. Nelson, 2017).

Though government administration of the environment has come under particular scrutiny in the case of western public lands and the management of wildfire, wildfire management is far from the only context in which government plays a significant role in managing the environment. It is therefore critical to understand how governments make decisions regarding environmental management. In general, economists either ignore this question by assuming governments are welfare-optimizing "social planners," or they have adopted political economy approaches to address this question. Yet while political economy approaches are well-suited to studying the formation of policy, outcomes may frequently be driven by policy administration. In the case of federal land management, bureaucratic land managers often have significant discretion in defining land (or wildfire) management strategies.

This dissertation presents three self-contained essays that use the example of federal wildfire management to study factors that affect decision-making among government environmental managers. In the first essay, I assess benefits of wildfire suppression in terms of avoided losses to structures. We know very little about benefits of wildfire suppression, in part because it is difficult to know how a fire would have spread in absence of suppression. To estimate benefits of wildfire suppression, I adopt a two-step strategy. In the first step, I use a novel spatial duration model, historical fire perimeters, and outputs from a state-of-the-art wildfire simulation tool to estimate the relative contributions of fire suppression effort and physical factors to the probability a wildfire will be extinguished. In the second step, estimates of the model are used to predict fire spread probabilities with and without suppression effort, and I compute estimates of avoided structure losses due to wildfire suppression based on these probabilities. While preventing losses to private property is a primary goal of wildfire management, I find that avoided losses to structures due to suppression are frequently substantially lower than suppression's costs, especially in the case of fires that begin in remote locations. Previous research has found that wildfire managers are frequently highly risk averse. My results are consistent with these findings, and suggest that in the case of wildfire management, government managers do not effectively optimize expected social welfare from wildfire suppression.

In the second and third essays, my collaborators and I explore consequences of behavioral biases among communities affected by wildfire management. While a large literature has studied the effects of behavioral biases on individual decision-making, in the second essay, we show that behavioral biases can also affect the decision-making of public agencies as well. In this essay, we focus on salience and government land management agency decisions over where to locate wildfire risk reduction projects. Salience is a common behavioral bias whereby people's attention is drawn to salient features of a decision problem, leading them to overweight prominent information in subsequent judgments. When agencies are influenced by public pressure, and when public risk perceptions are biased, resources may be allocated toward locations where risk is most salient, not to where those resources are most needed. We test whether salience increases or decreases allocation of government projects to reduce wildfire severity near wildland-adjacent communities. Even though the occurrence of a wildfire likely reduces the severity of future fires in the same area, it may increase the likelihood that fuels management projects are placed nearby if wildfire events strongly increase the salience of losses under future fires. We find strong evidence that the salience effects increase the likelihood of fuels management projects, and use robustness checks to eliminate competing explanations for our results.

The third and final essay uses behavioral bias-induced shocks to community demands for wildfire risk reduction projects to study differences in responsiveness to demographically-varying communities among government administrators. In general, we tend to believe that in a democratic system public participation in governmental decisions leads to better outcomes. However, recent research (e.g. Gilens, 2005) has argued that when preferences vary across groups, and when policymakers are differentially responsive to different groups, greater levels of responsiveness can lead to greater inequality. Focusing specifically on the case of wildfires and wildfire risk management in the western U.S., we find that when communities experience nearby wildfire events, it raises the salience of wildfire risk and leads agencies to place a greater number of wildfire risk reduction projects nearby. However, salience-based decision-making does not benefit all communities equally. We find that nearby fires increase rates of fuel treatment particularly among whiter and more highly educated communities. Although there is growing evidence of inequality in legislative representation, this is the first evidence we know of showing that public agencies perpetuate inequality, via the behavioral biases of the public.

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Chapter 2

Burning down the house: Wildfire and the benefits of responses to natural disasters

In recent years, the western U.S. and Canada have experienced a series of devastating wildfire events, including the Rim Fire in Yosemite National Park in 2013, the Fort McMurray wildfire in Alberta in 2016, and the devastating fires in Napa and Sonoma counties in California in October 2017. These wildfires are part of a pattern of increasingly frequent and severe wildfires in the region. Since the 1970s, wildfire frequency within the western U.S. has increased by over 500%, while area burned has increased by over 1200% (Westerling, 2016). As wildfires have become more pervasive, costs of managing them have increased correspondingly. Annual U.S. federal spending on wildfire suppression has approximately doubled in real terms over the past two decades (NIFC, 2017). In 2017, federal spending on wildfire suppression reached $2 billion for the first time.[1] While the

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

increase in wildfire spending has been especially dramatic, it parallels increases in federal disaster spending overall over the past several decades (Lindsay and McCarthy, 2015).

As the cost of managing wildfires grows, it becomes increasingly important to allocate responses to wildfires efficiently. The federal government—and in particular, the U.S. Forest Service—plays a central role in wildfire management within the western U.S. due to its extensive landholdings in the region and its role in funding state fire management programs.[2] In the early twentieth century, Forest Service policy required that all fires be extinguished as quickly as possible. Eventually, science supporting an ecologically beneficial role of wildfire caused a shift in official federal policy toward wildfires. However, while prescribed fire is now used in some cases to manage wildfire risk, and there are occasional allowances that wildfires within very remote wilderness areas be left to burn uncontrolled, aggressive suppression continues to dominate wildfire management (Franklin and Agee, 2003). This program of suppression is controversial. There is some evidence that wildfire managers are excessively risk averse in their responses to fires (Wilson et al., 2011; Wibbenmeyer et al., 2013; Thompson, 2014), and that a policy of indiscriminant wildfire suppression has eliminated potentially beneficial wildfires. In order to target wildfire suppression more efficiently, it is important to understand its costs and benefits, and how they vary across incidents. Yet we know very little about the benefits of wildfire suppression.

In this paper, I evaluate an important economic benefit of wildfire suppression effort: protection of private property. The benefits of responding to a natural disaster are defined as avoided losses due to the response. Therefore, estimates of the benefits of disaster response rely on an unobserved counterfactual: what would damages have been in absence of disaster response? To identify benefits of wildfire suppression, I adopt a

[2] Approximately 70% of federal wildfire spending is appropriated to the USFS (Thompson et al., 2015).

two-step approach. In the first-step, I estimate the effect of wildfire suppression effort on wildfire spread. In the second step, I conduct a counterfactual analysis in which I predict wildfire outcomes with and without wildfire suppression effort. I estimate avoided property losses due to suppression as the difference between estimated property losses under the two scenarios.

Identifying the effects of effort on fire outcomes is challenging because the strength with which government managers respond to a wildfire is expected to be endogenous to the intensity of the fire. Complicating matters further, both the physical factors that determine wildfire intensity and the effort that managers exert to suppress wildfires vary over space and over the evolution of a wildfire incident. I respond to these challenges in two ways. First, I adopt an explicitly spatial-dynamic approach to the estimation of effects of suppression effort. To account for natural and physical factors that affect fire spread, I make use of a fire simulation model developed by the U.S. Forest Service and used in the management of wildfire incidents. The fire simulation model, known as Minimum Travel Time (MTT), integrates spatial data as well as time-varying vegetation and winds data into predictions regarding wildfire behavior on the landscape. To estimate effects of wildfire suppression effort on fire spread, I condition on predictions of wildfire behavior. This effectively allows me to estimate effects of effort by contrasting fire spread across locations where wildfire behavior is similar, but effort is different.

In the counterfactual analysis, I find that avoided losses to private property vary substantially among wildfires. In some cases, avoided losses to private property may be hundreds of times the costs of suppression. On the other hand, there are many fires—especially fires in remote areas—for which the avoided losses to private property do not justify costs of suppression. Though there are both costs and benefits of suppression that are unaccounted for in this analysis, I argue that this suggests we may be over-allocating resources toward suppression of some remote wildfires.

This paper is one of the first studies to estimate benefits of responses to natural disasters, and is to my knowledge the first to focus on the benefits of mitigating natural disasters. The literature on costs of natural disasters is quite large (for a complete review see Field et al. 2012 or Kousky 2014). However, only recently have researchers begun to explicitly estimate benefits of responses to natural disasters.[3] Natural disaster damages can be averted through actions taken before an event (I refer to these responses as *adaptation*) or during (*mitigation*). In contrast to the few previous papers that have studied benefits of disaster response, I focus specifically on benefits of disaster mitigation. In particular, I focus on wildfire suppression, a form of disaster mitigation that affects the evolution of a wildfire event. Although mitigation is not possible for all types of natural disasters, it is not a unique feature of wildfire management. Other examples of disaster mitigation include deployment of flood control infrastructure and the management of disease outbreaks.

Wildfire suppression is a spatial-dynamic problem. This paper is among the first to empirically examine management of spatial-dynamic resources in a way that explicitly accounts for spatial-dynamics. Spatial-dynamic models are frequently intractable due to their high-dimensionality; therefore, much of the previous literature on spatial-dynamic resources has been theoretical in nature.[4] In the first step of the analysis, I develop a spatial duration model that accounts for the spatial-dynamic nature of wildfire management in a straight-forward and tractable manner.

I proceed by providing some background on wildfires and wildfire management within the western U.S. I then develop a simple model of wildfire management. This model is useful for motivating the empirical spatial duration model used in the first step of the

[3]For example, Hsiang and Narita (2012) study the capacity of countries to adapt to hurricanes.

[4]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)

analysis. It also provides qualitative predictions regarding the factors that should affect allocation of suppression effort. In section 2.3, I describe the methods used to estimate avoided private property losses due to fire suppression. This includes a description of the spatial duration model used to estimate the effect of effort on fire spread, as well a description of the way estimates of this model are used to evaluate avoided losses. In section 2.4, I describe the data used in the analysis, including data derived from USFS fire simulation models. I then present results from the first step of the analysis, followed by results from the counterfactual analysis. Finally, I conclude with a discussion of implications of the results for wildfire management.

2.1 Background

Wildfires—defined as uncontrolled non-structure fires occurring within wildlands—have increased in frequency and severity within in the western U.S. in recent years. Wildfires cause a variety of damages. They damage and destroy private property in their paths. For example, the northern California wildfires of October 2017 destroyed more than 8,000 structures, causing more than $3 billion in insured losses. Occasionally, wildfires result in losses of human life among fire fighters or ordinary citizens. Other damages result from the carbon dioxide and smoke emissions given off as wildfires burn. Carbon dioxide released each year by fires is equivalent to approximately 40% of global annual fossil fuel emissions (Van Der Werf et al., 2004). Though the majority of these emissions come from tropical forest fires, emissions from fires in temperate zones are nonetheless substantial; approximately 3-5% of California's annual carbon emissions come from wildfires (Gonzalez et al., 2015). Wildfire emissions also have important implications for human health. A large literature has evaluated the health effects of wildfire smoke and has found, for example, that wildfire smoke leads to increases in local hospital admissions (Moeltner et al., 2013), increases in early-life mortality (Jayachandran, 2009), and decreases in labor supply (Borgschulte et al., 2016).

Fires occur when heat, fuel, and oxygen—an assemblage known to fire scientists as the fire triangle—combine in the proper proportions. Of these elements, most of the recent increase in wildfire activity within the western U.S. can be attributed to increases, either due to climate or management, in the availability of fire-ready fuels. In the western U.S., climate change has led to earlier spring snowmelt, longer growing seasons, and warmer temperatures. Combined, these factors have encouraged growth of burnable fuels in western forests (Westerling, 2016). Further, wildfire suppression within the western U.S. has left the region's forests laden with fire-ready fuels (Allen et al., 2002; Schoennagel et al., 2004). Due to the build-up of fuels over time, ignitions are now more likely to develop in large, potentially damaging wildfires.

Because of its extensive land-holdings in the western U.S.,[5] the U.S. federal government plays a central role in managing wildfire in the region. At the beginning of the twentieth century, the primary goal of federal wildfire suppression efforts was conservation of resources, primarily timber. In the 1930s, the USFS adopted the "10 a.m." rule, which instructed forest rangers to attempt to extinguish all fires by 10 a.m. on the the morning following their ignition. Over the course of the twentieth century, scientific research established the importance of wildfire within forest ecology. In the 1978, the federal government established a policy of total fire management, which allowed some prescribed burns (planned burns intended to reduce fuels) and "let burns" on public lands.

Though current federal wildfire policy has been revised several times since 1978, it now states that "Response to wildland fires is based on ecological, social and legal consequences of the fire" (USDA and DOI, 2009). Managers are now expected to manage

[5]Federal lands comprise 47% of land in the western United States (Bui and Sanger-Katz, 2016).

wildfires in consideration of the range of values they affect, including watershed values, threatened and endangered species habitat, health impacts due to smoke, and other possible damages. However, it has generally been politically difficult to reduce wildfire suppression effort when private property is at-risk. In practice, wildfire managers' efforts are believed to be largely motivated by protection of homes and structures (USDA OIG, 2017; Gude et al., 2013; Gorte, 2013). Therefore, in many cases, wildfire suppresion policy today is indistinguishable from that under the 10 a.m. policy; when private property is at risk managers attempt to extinguish fires as quickly as possible.

Upon initially discovering a fire, fire managers will attempt to quickly extinguish it in what is known as the "initial attack." When fires escape managers' initial attempts at containment, they rely on three sets of tactics: direct attack, aerial attack, and indirect attack (NWCG, 2017). Direct attack includes tactics in which managers 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 setting fire to fuels in the main fire's path while wind conditions are favorable. Finally, fire managers can take advantage of pre-existing fuel breaks, such as roads.

To guide their use of these tactics, fire managers rely on knowledge of fire behavior and weather, as well as a series of sophisticated wildfire simulation software tools, such as Farsite (Finney, 1998) and FSPro (Finney et al., 2011). Wildfire simulation models incorporate data on physical topography, data vegetation and fuels, and weather data. Within a model of fire behavior, these data allow fire simulation models to predict how the three elements of the fire triangle—heat, fuel, and oxygen—will come together to influence wildfire spread. Fire simulation models can also predict important characteristics of wildfire behavior, such as the rate of fire spread and the intensity (measured in heat loss per unit time). These predictions help fire managers choose how to allocate resources in order to achieve management objectives such as defense of private property.

2.2 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, I 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, I 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, I write the probability the fire is extinguished at point s as $\lambda(e_{s\ell}, r_{s\ell})$, and assume $\lambda(\cdot)$ is decreasing in fuels, and increasing in effort. Additionally, I 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. I 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:

$$y_{s+1,\ell} = \begin{cases} 0 \text{ with prob. } 1 - \lambda(e_{s\ell}, r_{s\ell}) \text{ if } y_{s\ell} = 0 \\ 1 \text{ with prob. } \lambda(e_{s\ell}, r_{s\ell}) \text{ if } y_{s\ell} = 0 \\ 1 \text{ if } y_{s\ell} = 1 \end{cases} \tag{2.1}$$

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 $s\ell$.

I 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:

$$V_s(\boldsymbol{y}_{\ell s}, b_s) = \max_{e_s} - \sum_{\ell=1}^{L} (1 - y_{\ell s})u(\mathbf{x}_{s\ell}) + \beta \mathrm{E}_y \left[V_{s+1}(\boldsymbol{y}_{s+1}, b_{s+1}) | \boldsymbol{e}_s \right] \tag{2.2}$$

subject to equation 2.1, $b_{s+1} \geq 0$, and the law of motion for b_s. To solve this problem, the manager will choose $\mathbf{e}_s^*$ such that:

$$\lambda_e(e_{s\ell}^*, r_{s\ell})\mathrm{E}\big[\frac{\partial V_{s+1}}{\partial y_{s+1,\ell}}(\mathbf{e}_s^*)\big] = c(\mathbf{z}_{s\ell})\mathrm{E}\big[\frac{\partial V_{s+1}}{\partial b_{s+1}}\big] \tag{2.3}$$

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 2.3 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. 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.

2.3 Empirical model

2.3.1 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 2.2, I adapt methods from duration analysis to a spatial setting. Consider a fire burning in a single direction along a featureless line. 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, I 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. As in the theoretical model, I model the extinction probability as depending on natural characteristics (r_s) and fire suppression effort (e_s), both of which vary over space. I then model effort as depending on the characteristics of at-risk assets in the fire's path and estimate how these factors affect extinction probability.

I 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:

$$F(s) = 1 - \exp\big[- \int_0^s \lambda(s, e_s, r_s; \theta) ds \big]. \tag{2.4}$$

Since fires potentially spread in 360 degrees from their points of origin, I divide the landscape around each ignition into L directions of spread, where directions of spread are indexed by ℓ. I then divide each direction of spread into distance intervals, where each interval m defines a grid cell spanning the distance $(a_{m-1}, a_m]$ for $m = 1, \ldots, M$. I define y_m as equal to 1 if the fire stops burning within a_{m-1} and a_m 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.

I apply grouped duration data methods (e.g. Sueyoshi, 1995) because my measure of fire spread distance is observed within discrete distance intervals. Using equation 2.4, the probability a fire is observed to stop burning within the interval $(a_{m-1}, a_m]$ along direction of spread ℓ can be written:

$$\Pr(y_m = 1 | y_{m-1} = 0, m \leq M) = 1 - \exp\big[- \int_{a_{m-1}}^{a_m} \lambda(s, e_s, r_s; \theta) ds \big]. \tag{2.5}$$

Under the assumption that factors affecting extinction probability are constant within interval $m\ell$, I define $\mathbf{w}_{m\ell}$ to be a vector describing e_s and r_s within the interval. I 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 $(m-1, m]$. I 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:

$$\mathcal{L}_\ell(\theta|M_\ell) = \big(1 - \alpha_m(\mathbf{w}_{m\ell};\theta)\big) \prod_{m=1}^{M_{\ell-1}} \alpha_m(\mathbf{w}_{m\ell};\theta), \tag{2.6}$$

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. Under the further assumption that $\alpha_m(\mathbf{w}_{m\ell};\theta)$ is independent across fires and directions of spread conditional on $\mathbf{w}_{m\ell}$, the overall likelihood function over L directions of spread and K fires can be written:

$$\mathcal{L} = \prod_{k=1}^{K}\prod_{\ell=1}^{L}\prod_{m=1}^{M_\ell} \big(1 - \alpha_m(\mathbf{w}_{m\ell};\theta)\big)^{y_{m\ell k}} \alpha_m(\mathbf{w}_{m\ell};\theta)^{(1-y_{m\ell k})}. \tag{2.7}$$

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). Fire extinction probabilities are not independent across directions-of-spread. 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 2.3.3, I discuss how I test the model's robustness to non-independence among fire spread directions.

2.3.2 Specification of spread-distance model

In order to estimate equation 2.7, I assume extinction probability is of the form:

$$\lambda(s, e_s, r_s;\theta) = \exp\big(e_{m\ell} + r_{m\ell}\big)\lambda_0(s) \tag{2.8}$$

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, I 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 $\gamma_m = \ln \int_{a_{m-1}}^{a_m} \lambda_v dv$, and using equation 2.5, extinction probability can be written:

$$\alpha_m(\mathbf{w}_m;\theta) = \exp\left[-\int_{a_{m-1}}^{a_m} \exp(e_{m\ell} + r_{m\ell} + \gamma_m)\ dv\right] \equiv F\big(e_{m\ell} + r_{m\ell} + \gamma_m\big). \tag{2.9}$$

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. Distance-interval fixed effects are captured by γ_m; therefore, I make no assumptions regarding the form of duration dependence.

According to the theory developed in section 2.2, 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 assets further in the direction of spread that are protected by suppression of the fire at that location. Therefore, I write effort as:

$$e_{m\ell} = \sum_{m=0}^{\bar{m}} \beta^m \mathbf{x}_{m\ell} - \mathbf{z}'_{m\ell}\boldsymbol{\delta} \tag{2.10}$$

where benefits of suppression include "spatial leads" of assets-at-risk ($\mathbf{x}_{m\ell}$) up to $\bar{m}$ cells away and suppression costs are function of the vector $\mathbf{z}_{m\ell}$ within cell $m\ell$. In the theory developed in section 2.2, effort can depend on physical landscape factors $r_{m\ell}$ if λ_{er} is not equal to zero. Therefore, I also test models that include spatial leads of natural factors affecting fire spread. Including leads for these variables does not influence results.

In order to account for the effects of physical factors on fire spread, I rely on simulated variables derived from a USFS fire simulation model. These variables, rate of spread and fire intensity, are summarized in the vector $\mathbf{v}_{m\ell}$. Rate of spread and fire intensity do not necessarily contribute in to extinction probability in a linear way. For example, a low rate of spread may only contribute to the probability a fire stops spreading only when rate of spread is very low. Therefore, I allow $\mathbf{v}_{m\ell}$ to influence the complementary log-log index function through the non-linear function $g(\cdot)$. In summary, I specify the complementary log-log distribution I estimate as:

$$F\big(\sum_{m=0}^{\bar{m}} \beta^m \mathbf{x}_{m\ell} - \mathbf{z}'_{m\ell}\boldsymbol{\delta} + g(\mathbf{v}_{m\ell}) + \gamma_m\big). \tag{2.11}$$

2.3.3 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 density 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 rate of spread accounts 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 2.7 requires the independence assumption, therefore violations of independence may bias both coefficient and standard error estimates. I adopt several strategies to test the sensitivity of results to violations of this assumption. First, I estimate the model using a linear probability and compare the resulting coefficient estimates to marginal effects from equation 2.11. Since predicted probabilities from the linear probability model may fall outside the 0,1 interval, and ultimately I will use the estimated model to predict fire spread probabilities, the LPM is not a satisfactory alternative to equation 2.11. However, comparing coefficients from the LPM to marginal effects estimated from equation 2.11 provides a test of the results' sensitivity to violations of the independence assumption. Correlation in spread distances among spread directions should decrease as the number of directions of spread within each fire is reduced. Therefore, as a second test, I vary the number of directions of spread L within each fire and test how results depend on how finely the data are partitioned. Third, in my preferred specification of equation 2.9 I include fire-specific fixed effects. 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. Finally, to ensure appropriate inference under violations of the independence assumption, I cluster standard errors by fire (Cameron and Miller, 2010).

2.3.4 Counterfactual analysis

I use results from the estimation described above to estimate benefits of wildfire suppression. Benefits of wildfire suppression are equal to the difference between expected losses under the current suppression regime and expected losses under a regime with no suppression. Letting ψ_ℓ represent the benefits of wildfire suppression within direction ℓ, this quantity can be calculated as:

$$E(\psi_\ell) = \sum_{m=1}^{M} \left(\pi_{m\ell}^{N}\mu^{N} - \pi_{m\ell}^{S}\mu^{S}\right) \times h_{m\ell},$$

where $\pi^S_{m\ell}$ and $\pi^N_{m\ell}$ represent the probability that fire reaches cell $m\ell$, with and without suppression respectively and $h_{m\ell}$ denotes the total value of structures within the cell. The parameters μ represent the fraction of total structure value that is expected to be lost conditional on fire reaching the cell. Since some portion of fire suppression effort may be allocated to directly defending structures, μ is allowed to vary by suppression regime so that μ^S represents the rate of structure loss under the current suppression regime and μ^N represents the rate of loss under no suppression.

Estimates of equation 2.11 can be used to calculate fitted probabilities that fire will reach each cell. Under the current wildfire suppression regime, the expected probability with which fire will reach each cell $m\ell$ can be written:

$$\hat{\pi}^N_{m\ell} = 1 - F\big(\hat{e}_{m\ell} + g(\widehat{\mathbf{v}_{m\ell}}) + \hat{\gamma}_m\big) \tag{2.12}$$

where:

$$\hat{e}_{m\ell} = \sum_{m=0}^{\bar{m}} \mathbf{x}'_{m\ell}\hat{\boldsymbol{\beta}}^m - \mathbf{z}'_{m\ell}\hat{\boldsymbol{\delta}} \tag{2.13}$$

Under a zero suppression effort regime, the probability fire reaches cell $m\ell$ can be written:

$$\hat{\pi}^S_{m\ell} = 1 - F\big(g(\widehat{\mathbf{v}_{m\ell}}) + \hat{\gamma}_m\big). \tag{2.14}$$

Using these estimated probabilities, I construct the following estimator for benefits of suppression within direction of spread ℓ:

$$\hat{\psi}_\ell = \sum_{m=1}^{M} \big(\hat{\pi}^N_{m\ell}\mu^N h_{m\ell} - \hat{\pi}^S_{m\ell}\mu^S h_{m\ell}\big). \tag{2.15}$$

When $h_{m\ell}$ and the parameters μ are known, this estimator can be used to calculate the expected benefits of fire suppression for fires within the sample. This benefit can be compared to costs of fire management to assess the net benefits of fire suppression.

2.4 Data

2.4.1 Spread-distance model data

To estimate the model of fire spread-distance, I use three primary categories of data: data describing fires and ignition locations, data describing determinants of fire suppression effort, and data describing natural factors that affect fire spread. 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. It is possible that the availability of only relatively large wildfires induces selection bias. Wildfires may fail to reach the 1000-acre threshold for inclusion in the MTBS data set because they are more responsive to suppression, or because they are relatively weak. If included fires are disproportionately non-responsive to suppression, then the estimated effect of suppression may be biased downward. Nonetheless, the estimated effect of suppression can be viewed as a local average effect of effort among fires that escape initial containment and grow to be greater than 1000 acres. Because I estimate benefits of suppression only for fires that reach the 1000-acre threshold, I may omit fires for which suppression is most worthwhile (for example, if costs of suppression are substantially smaller on small wildfires). If so, the true distribution of net benefits may include a greater number of fires for which fire suppression is worthwhile. But though the estimated distribution of net benefits from fire suppression will be biased, the estimated net benefits from any individual wildfire will not be biased.

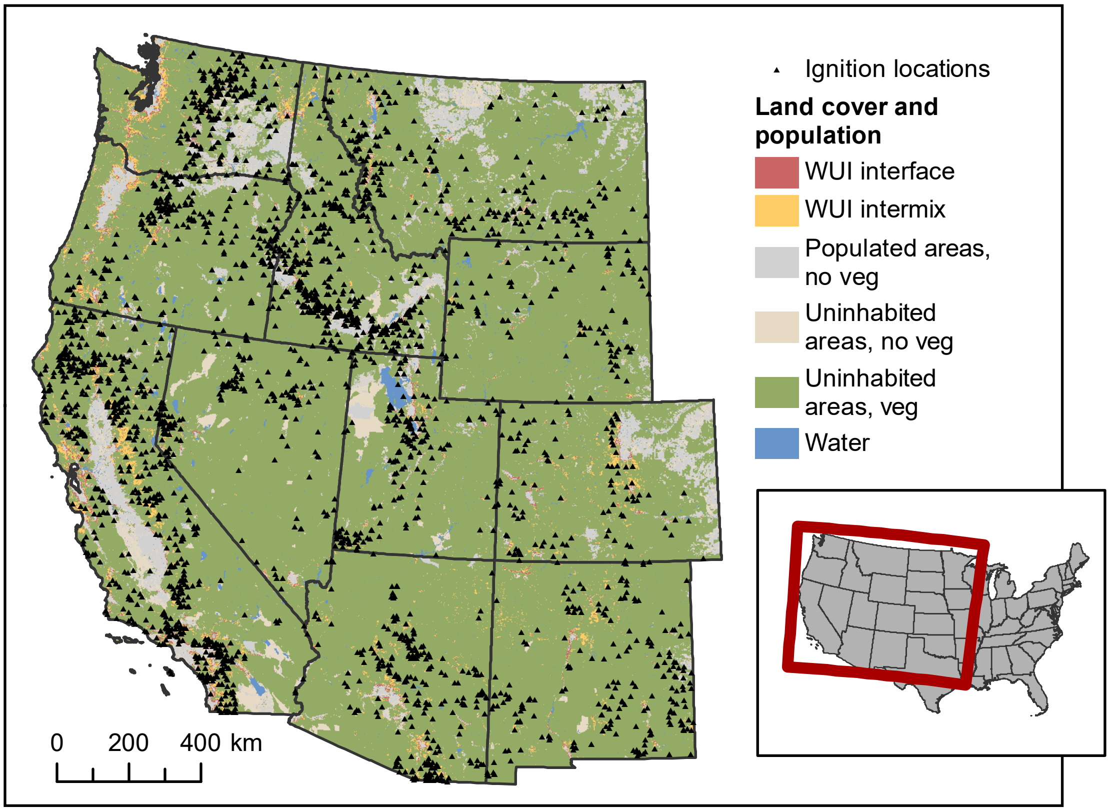
Ignition locations are due to Short (2017), who compiled a comprehensive database of wildfires within the U.S. from 1993-2015 using a variety of federal, state, and local sources. Fires within the database include coordinates of each fire's point of origin to within 1 km. Short (2017) includes even small ignitions that never grew to be threatening fires. I restrict my attention only to the set of fires large enough (generally greater than 1000 acres) to be mapped by MTBS. Further, I focus on fires whose ignitions were within 10 km of wildland urban interface, as mapped by Radeloff et al. (2005),[6] and which occurred in the western U.S. in years 1999- 2015. I restrict the sample to fires near wildland urban interface areas because I am interested in benefits of fire suppression, which should be largest for these fires. I focus on the western 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. Under these restrictions, the sample contains 2,119 fires, the locations of which are displayed in Figure 2.1.

To adapt the empirical model from the previous section to the data, I divide the area surrounding each wildfire ignition point into L directions of spread. An example is provided in Figure 2.2. In the primary set of results, L is equal to 24, and each direction of spread has an angle of 15 degrees, though I check robustness of my results to varying values of L. I 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. I 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 the centroid of the next cell. All prior cells (those nearer to the ignition point) within the direction of spread are coded as burnt ($y_{m\ell} = 0$).[7] I refer to the distance

[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).

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

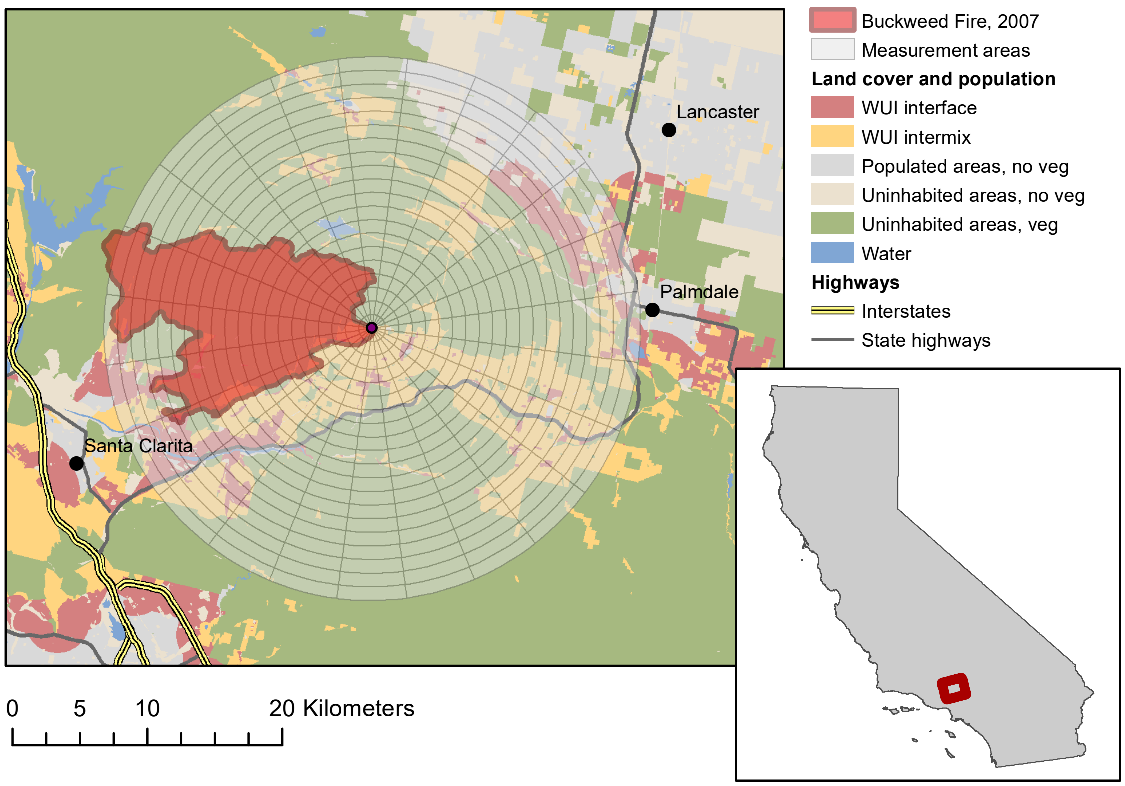
Figure 2.1: Geographic distribution of fires within the sample



interval at which the fire is first extinguished within each direction as interval M_ℓ, and I 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. I ignore such cases and treat fires as remaining extinguished once they have first been extinguished within a direction of spread.[8] Figure 2.3 shows the distribution of fire spread distances. For approximately 85% of spread-directions, fires are extinguished within 5 km of the ignition point. Fewer

[8] An alternative would be to code $y_{\ell m}$ 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.

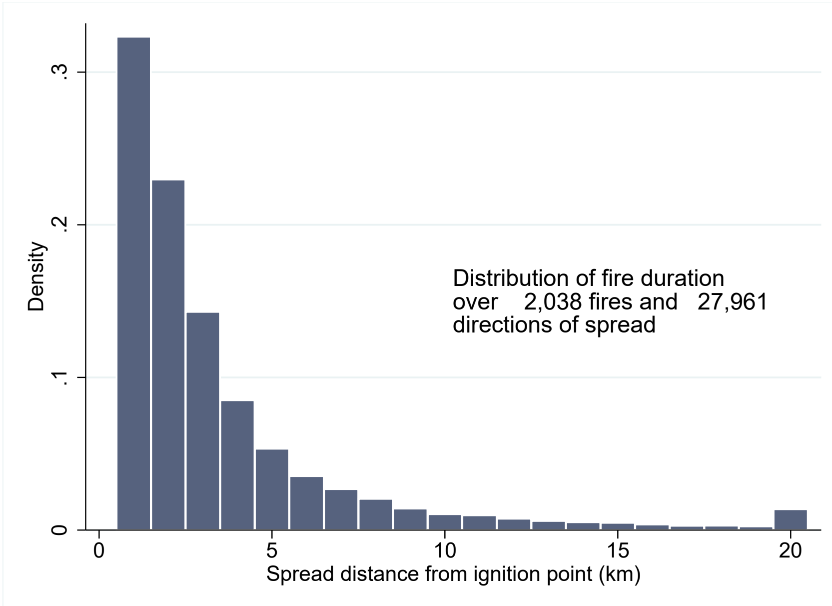
Figure 2.2: Illustration describing the construction of the data set



than 1% of spread-directions are censored by the maximum distance of 20 km.

Fire suppression 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 due to populations at risk, I use U.S. Census data collected at the block and tract-level. Population and housing variables are available for the 2000 and 2010 censuses at the block level. Other demographic variables, including income and education variables, are available only at the Census tract-level. To map Census block-level and tract-level data to the circular grids surrounding each ignition point, I assume that populations are uniformly distributed within each Census block, and that Census blocks are demographically uniform within each tract. Because I lack data on home values for the 1999-2015 sample of

Figure 2.3: Histogram of fire spread distances



fires throughout the western U.S., I rely on Census per capita income data to provide a proxy for home values. As can easily be seen in Figure 2.2, 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 and Wilen, 2012). Consistent with this feature of fire spread, I use area-dependent measures to capture both benefits and costs of controlling fire within a grid cell. To proxy for the number of homes in a cell, I use population density. As a measure of the total value of homes within each cell, I use population multiplied by per-capita income, which I refer to as "total income." To allow that fire managers may undertake greater suppression effort on behalf of higher income residents, I also per capita income. In its first panel, Table 2.1 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

Table 2.1: 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
Demographic vars.					
Total population	8.38	40.3	80.9	132	65.2
Population density (persons/sq. km)	34	63.9	77.2	90.3	66.2
Total income (2009 USD thousands)	181	807	1,651	2,612	1,309
Per capita income (2009 USD thousands)	23.3	23.3	23.3	23.2	23.3
Percent high school graduate	80.1	80.2	80.1	80.1	80.1
Percent college graduate	18	18	17.9	17.9	17.9
Other values at risk					
Contains major road	.0604	.0987	.138	.169	.116
Avg. watershed importance rating (0-100)	31.9	31.8	31.7	31.5	31.7
Percent TES habitat (non-stream)	13.4	11.9	11.1	10.7	11.8
Percent within 0.5 km of TES habitat (stream)	3.83	3.5	3.33	3.28	3.48
Cost vars.					
Percent within 0.5 km of roads	56.9	58	57.5	57	57.3
Avg. topographic ruggedness index	21.6	19.6	19.2	18.6	19.7
Fire spread vars.					
Simulated rate of fire spread (chains/hour)	1.72	1.6	1.54	1.5	1.59
Simulated fire intensity (kW/hour)	270	298	293	285	287
Number of obs.	219,933	219,192	218,345	217,421	874,891

Note: TES refers to threatened and endangered species.

large, and therefore 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 concern of fire managers, they may also be concerned with protecting a variety of other assets, including watersheds, threatened and endangered species habitat, and roads. An important management objective of forest managers is to protect watershed values. Fires can impact watersheds by increasing runoff and reducing water storage. I measure the watershed value of each cell by multiplying its area by a spatially-weighted average of its watershed significance, based on a 0-100 rating provided by USDA (2017). To control for the influence of threatened and endangered species habitat on suppression effort, I construct two measures using geospatial data describing locations of critical habitat (USFWS, 2017). I measure the area within each cell classified as critical habitat for terrestrial species, and I measure the area within each each cell that is within 0.5 km from riparian species. Fire managers may be averse to closing major roads due to fire. Therefore, I construct an indicator variable describing whether a primary or secondary road crosses each cell.[9]

To account for differences in the cost of fire suppression over space, I collect data on accessibility and topographic ruggedness. Accessibility is measured as area within each cell that is within 0.5 km of a road. I measure costs associated with ruggedness by calculating the average topographic ruggedness index (TRI) within each cell using 30 m resolution digital elevation model (DEM), and multiplying average TRI by the cell's area. TRI measures the variation in elevation among a pixel and its neighbors (Riley, 1999; Nunn and Puga, 2012). Another important factor affecting cost of effort is the availability of personnel and equipment resources. Among the models I estimate in the next section are models including fire-level fixed effects. Fire-level fixed effects should account for differences in availability of resources, since availability of resources generally should be same within a given fire.

Finally, I control for natural factors affecting fire spread through inclusion of outputs from a model of fire spread. The USFS has developed a variety of fire simulation software

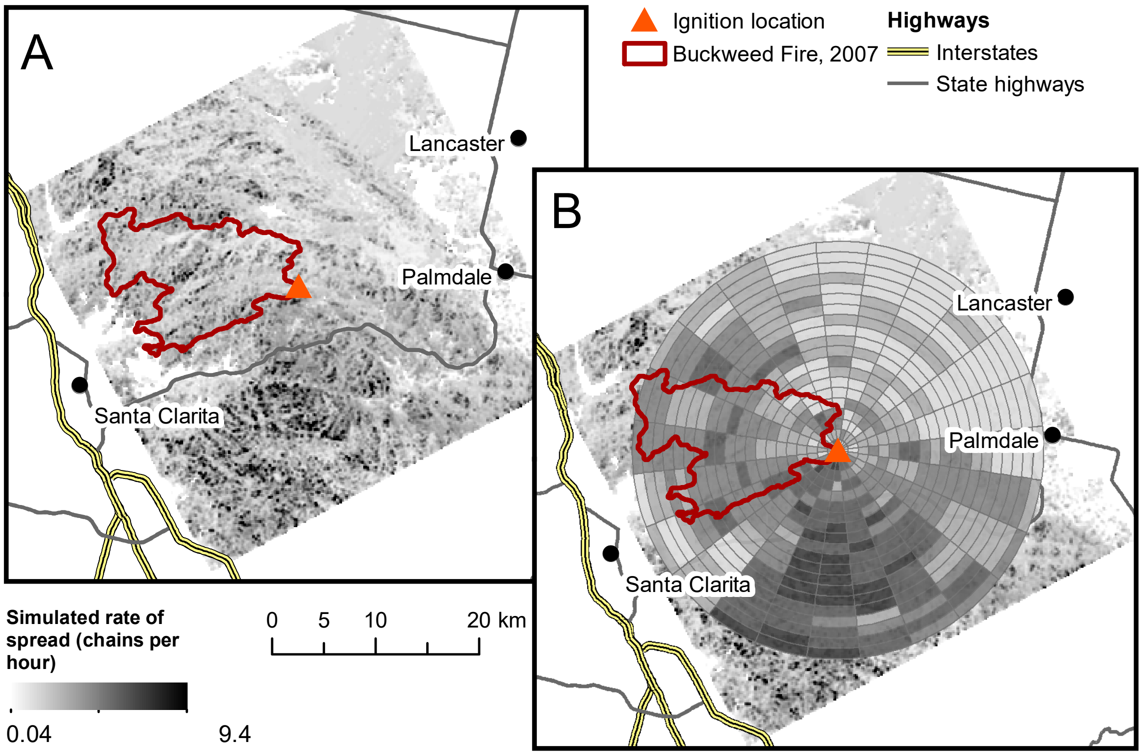
[9]Primary roads are defined as divided, limited access state highways or interstate highways. Secondary roads are other highways belonging to the U.S. highway, state highway, or county highway systems.

(including Farsite, Flammap, and FSPro), each of which varies in its applications within fire management. To simulate fire spread, I use the Minimum Travel Time (MTT) model, which is the foundational fire simulation model underlying a variety of these programs, including Flammap and FSPro. Rather than explicitly predicting how a fire perimeter will expands over 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 in exchange for relatively low computational cost (Finney, 2002). MTT takes as inputs features of the landscape such as elevation, slope, and aspect, as well as characteristics of vegetation on the landscape. An MTT simulation also includes as input a guess as to initial fuel moisture conditions (the model then allows fuel moistures to evolve over the course of the fire) and a wind direction and wind speed. Topographic data and time-varying vegetation and fuels data were collected from the Landfire project (Landfire, 2014), which provides remotely-sensed landscape data at a 30 m resolution.[10] I collected observed wind speed and wind direction at the time of each ignition from its closest Remote Automated Weather Station (RAWS station).

I simulated fire spread for each of the 2,119 wildfires in my sample. Rather than limit the duration of each simulated fire, I allowed each fire to entirely consume the landscape within 20 kilometers of its ignition point. Allowing the landscape to be entirely consumed by fire generates a series of landscape-wide measures describing how fire would be expected to burn within a given pixel, conditional on reaching that pixel. I use simulated

[10]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. I 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.

Figure 2.4: Illustration of fire simulation output



fire intensity and simulated rate of spread as predictors of fire extinction probability. Fire intensity measures the rate at which energy is released due to the consumption of fuels. High intensity is characteristic of hot fires that burn in the upper canopy of the a forest, whereas low intensity fires frequently burn on grasslands or within the forest understory. Rate of spread measures the speed at which a fire's flaming front moves across the landscape. An example output from MTT is provided in panel A of figure 2.4. Darker pixels correspond to locations where fire is expected to spread more rapidly. Panel B illustrates that MTT outputs are averaged over circular grid cells to yield a grid-cell level measure of rate of spread.

In its lower panels, Table 2.1 summarizes how non-demographic values-at-risk, cost, and fire spread variables vary 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. Watershed importance and amount of endangered species habitat tends to decrease with distance from the ignition point, but prevalence of major roads increases. As distance from the ignition point increases, fires are expected to burn more slowly and cost of suppression becomes lower.

2.4.2 Counterfactual analysis data

To apply spread-distance model results to the estimation of benefits of fire suppression, $h_{m\ell}, \mu^N$, and μ^S must be known. To estimate these variables I draw on two additional sources of data. The value of structures within each grid cell is based on property-level county assessor's data from CoreLogic, Inc. for the entire state of California in years 2010 and 2011.[11] I overlay the property-level data set against each fire's circular grid, and I calculate the sum total of assessed structure values within each cell.[12] Property values may quite likely be influenced by the occurrence of a fire. In order to ensure that property value estimates are not affected by fires in my sample, I focus on fires occurring after 2011. As well, data on costs of suppression and structures destroyed are not available for 2014 and 2015. Therefore, I focus on estimating benefits of wildfire suppression for 47 fires occurring in California between 2012-2013.

Because not all structures within the boundary of a wildfire are destroyed, I estimate the fraction of structure value lost conditional on fire burning the cell (the parameters μ). I collect the number of structures within each wildfire perimeter and the number of structures destroyed for each of the 2012-2015 California wildfires. The number of structures destroyed comes from situation reports (SIT-209 reports) submitted to the

[11] These data were generously provided by Randy Walsh and are used under an agreement with Duke University Department of Economics.

[12] Structure values for each property are calculated as the difference between estimated property value and assessed land values

interagency Incident Command System, which coordinates allocation of fire management resources across incidents. Situation reports frequently, but not always, include estimates of the number of structures destroyed on a given fire. I use these numbers, with the number of properties falling inside each wildfire perimeter, to construct a fraction of structure value within the perimeter that is destroyed. This fraction provides an estimate of μ^S, the rate of structure value loss under the current suppression regime. The rate of structure loss under no suppression loss is not observed, therefore I calculate net benefits for various value of μ^N. First, I assume that under no suppression, structure value is lost at the same rate it is lost in the current suppression regime. This likely underestimates the value of structures that would be lost under no suppression, since some suppression resources may be used to directly defend structures. An alternate assumption is that 100% of structure value within burnt cells is destroyed by fire. This is likely an overestimate of losses but provides an upper bound for estimates of lost structure value under no suppression. To assess whether avoided structure losses justify costs of suppression, I use suppression cost estimates, which are also drawn from wildfire situation reports.

2.5 Results

2.5.1 Spread-distance model results

Tables 2.2 and 2.3 provide estimates of the effects of suppression effort and natural fire spread variables, respectively, on extinction probability. For variables associated with fire suppression effort, I report marginal effects calculated at the means of the explanatory variables. Fire managers are assumed to consider assets at risk up to 3 km in advance of a fire's current point of spread; however, second and third spatial leads are, in general, not statistically significant from zero and so they are omitted from the table. This could be evidence that, in spite of the model developed in section 2.2, managers are relatively short-sighted and only consider assets that are relatively directly in a fire's path. Another possible interpretation is that production of extinction probability is convex in effort; for example, partially constructed fire breaks may be ineffective. In this case, fire managers might focus their attentions and effort constructing fire breaks just ahead of important assets in the fire's path. A third possible interpretation of this result is that beyond the first lag, spread directions are not accurate reflections of where managers believe fires will spread. The paper's empirical strategy imposes a significant amount of structure on patterns of fire spread. Fire managers may have beliefs about where fires will spread that are not reflected in the linear directions-of-spread. Future work could use fire simulation models to develop landscape-based directions-of-spread.

Column 1 of Table 2.2 omits fire spread controls and estimates fire extinction probability as a function only of assets at-risk. Column 2 adds fire spread controls, and column 3 adds fire fixed effects. Fire fixed effects control for fixed differences in extinction probability within directions-of-spread and across fires. For example, fire fixed effects might control for unobserved differences in suppression costs across fires. They may also help control for unobserved differences in fuel moisture (which affects how readily vegetation will burn) due to the time of year and precipitation. Within column 3, the preferred specification, a variety of suppression effort variables are significantly different from zero in the focal cell or the first spatial lead. Marginal effects for explanatory variables within the focal cell indicate variables' marginal effect on the probability fire will stop spreading before it reaches the centroid of the next cell within the direction of spread. For example, when fire reaches the centroid of a populated cell, it is 3.3 percentage points more likely to stop burning before it reaches the next cell's centroid than it would have been within an unpopulated cell. First spatial leads reflect the marginal effect explanatory variables within the next cell in a given direction-of-spread have on the probability fire will stop spreading before it reaches the centroid of the next cell. This explains why in some cases the first spatial lead has a marginal effect with greater statistical significance or greater magnitude. Focal cells where fires are extinguished may frequently be majority burnt; at the very least, their centroid is burnt. In contrast, spatial leads of cells in which fires are extinguished have unburnt centroids.

In general, marginal effects within Table 2.2 accord with expectations. Fires are 6.7 percentage points more likely to be extinguished when they are burning toward populated grid cells. When population within the leading cell further increases by 100, the probability the fire will be extinguished increases by 4.4 percentage points. Increases in population density by 1 person per square kilometer within focal and leading grid cells are associated with 0.01 percentage point increases in extinction probability. Interestingly, both total income and per capita income have no discernable effect on probability of extinction. Indeed, if anything, increases in income are associated with decreases in the probability of fire extinction. These results imply that fire managers do not preferentially protect higher income areas or areas where the value the total value of the housing stock is greater. Rather, it appears that effort is largely motivated by preventing fire from spreading into populated areas. Fires are also substantially more likely to stop spreading before they reach cells containing major roads. While this large coefficient may reflect managerial aversion to closing major roadways, it is also possible that roadways provide a fire break that is not adequately captured by the fire spread model. Therefore, I have tested the sensitivity of counterfactual analysis results to the inclusion of the major road indicator within the vector of variables determining effort. Excluding the major road indicator from the effort vector does not substantively change the results of the couterfactual analysis. They are also more likely to stop burning as they approach riparian threatened and endangered species habitat, though they are somewhat less likely to stop burning prior to reaching non-stream sensitive habitat. Watershed importance appears to have no effect on probability of extinction. Of the two cost variables, only the percentage of the cell near road is statistically significant in the preferred specification. Fire is 2.9 percentage points more likely to be extinguished within cells with 10 percentage points more area within 0.5 km of a road.

In columns 2 and 3 of Table 2.2, I control for effects of physical factors (landscape, fuels, etc.) on fire spread by allowing fire simulation outputs (rate of spread and fire intensity) to each affect the complementary log-log index function in a cubic function. This is to allow for the fact that the effect these variables have on probability of extinction may vary depending on their value. Since it would not be meaningful to report separate marginal effects for the linear, quadratic, and cubic terms for each polynomial, I instead report coefficients within Table 2.3. Columns 1 and 2 in Table 2.3 report polynomial coefficients for fire spread variables from the regressions in column 2 and 3 of Table 2.2, respectively. For the preferred specification, each of the polynomial coefficients is strongly significant. This indicates that rate of spread and fire intensity have significant effects on probability of extinction, and that these effects depend on the value of those variables. For the range of values in the sample, simulated rate of spread has a negative effect on probability of extinction, and simulated fire intensity has a positive effect on probability of extinction. The effect of simulated rate of spread is of the expected sign. As shown in Figure 2.4, simulated rate of spread is low within developed areas or areas with no vegetation; therefore, the negative effect of rate of spread on probability of extinction indicates that the variable is appropriately capturing the effects of fuels on extinction probabilities. On the other hand, the marginal effect of intensity on extinction probability is not negative, as would be expected. The positive effect of intensity on fire extinction may capture the fact that fires tend to stop their spread on ridgelines, where fire intensity tends to be high (Moritz, 2017).

As discussed in section 2.3, the empirical model is based on an assumption that spread-distances are independent across directions-of-spread within fires. Since this assumption is likely false, I provide a series of tests of robustness checks intended to test whether results depend on this assumption. First, I estimate the corresponding model using a linear probability model. Unbiasedness of OLS does not depend on independence among observations, therefore this provides a test for whether violations of the independence assumption bias estimates reported in Table 2.2. Results from the linear probability model are reported in column 1 of Table 2.4. Coefficients are very similar to marginal effects from the preferred specification, indicating that violations of the independence assumption do not strongly influence results. In columns 2 and 3, Table 2.4 reports estimates of equation 2.11 using logit and probit models, respectively. These models test sensitivity of results to the specification of the hazard function, since it is the choice of an exponential proportional hazard model that implies the complementary log-log distribution. Results are not sensitive to the choice of binary response model.

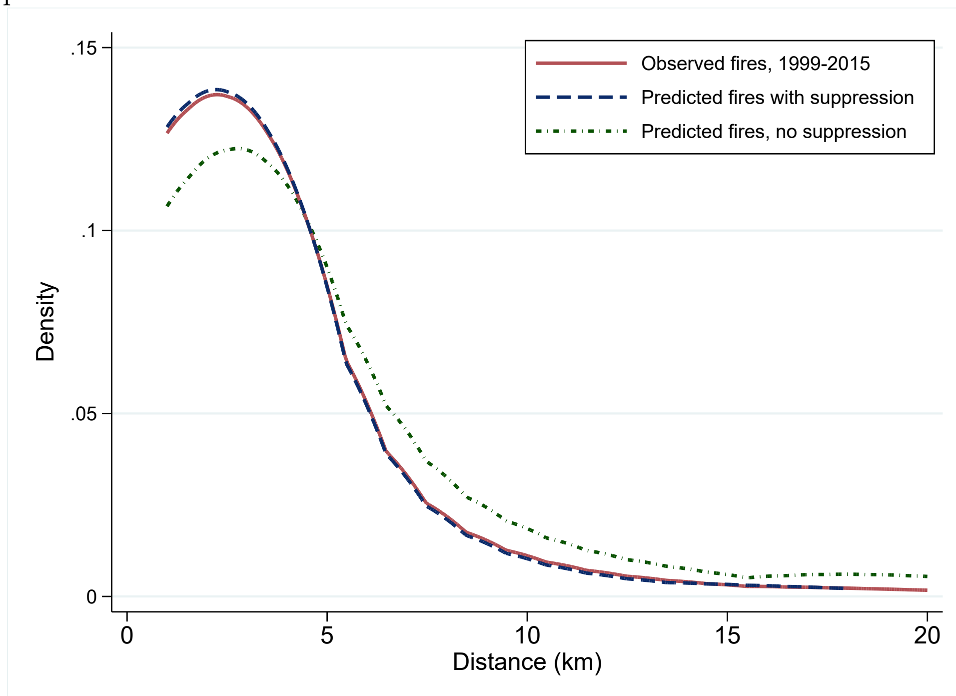
Since the correlation between directions of spread should decrease as the number of directions of spread within each fire decreases, I also test the sensitivity of results to varying the number of directions-of-spread that surround each fire ignition. In Table 2.5, I report marginal effects for explanatory effort variables when the data set is constructed with 48, 12, and 6 directions-of-spread for each fire. The number of directions can be increased or decreased from the number (24) used in the preferred specification without substantially altering results. If the number of directions-of-spread is sufficiently small, some results become statistically insignifcant—in part because the the number of observations decreases with the number of directions. Even in this case though, signs and magnitudes of coefficients remain broadly similar, providing additional evidence that results are robust to violations of the independence assumption.

2.5.2 Counterfactual analysis results

Using the full sample of fires across the western U.S., I calculate fitted fire spread probabilities using equations 2.14 and 2.12, and coefficients from column 3 of Table 2.2. These probabilities are used to predict fire spread distances with and without fire suppression. Before proceeding to the counterfactual analysis, I use these probabilities to predict fire spread distances for each of the fires in the western U.S. sample. I predict fire spread with and without suppression 1,000 times for each fire. Figure 2.5 shows a kernel density plot of the distributions of simulated fire spread distances with and without suppression, plotted against the observed distribution of fire spread distance within the sample. The distribution of predicted fire spread distances under suppression matches the observed distribution of fire spread distances precisely, which indicates the model fits the data well. When fires are not suppressed, I predict they spread further on average. While most fires are extinguished quickly, the number of far-spreading fires is greater when fires are not suppressed. The counterfactual analysis studies the degree to which this difference is economically meaningful, and the degree to which it justifies suppression spending.

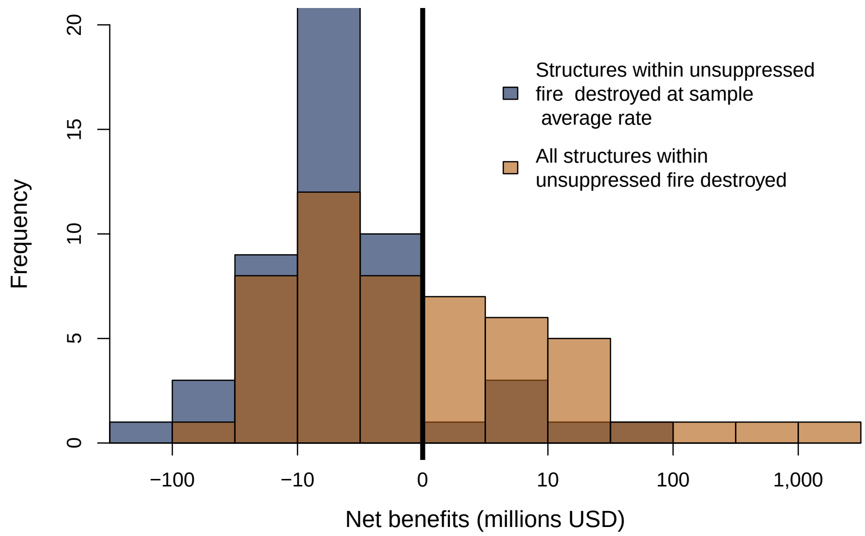
Table 2.6 summarizes net benefits, calculated as estimated benefits from equation 2.15 less estimated costs of suppression from wildfire situation reports, for 47 California wildfires in years 2012 and 2013. Net benefits are calculated using three alternative loss rates within unsuppressed fires: the observed sample loss rate (0.04), 0.5, and 1. Even when the loss rate is assumed to equal 1, median net benefits are negative. However, the distribution is highly skewed with some fires having very high net benefits of suppression. Assuming a loss rate of 1, suppression on one fire within the sample is estimated to have yielded benefits of greater than $2 billion. Figure 2.6 illustrates the distribution of the log of net losses and benefits under an the observed sample loss rate and a loss rate of 1.

Figure 2.5: Kernel density plot of the distribution of fire spread distances for observed and predicted fires. Kernel density functions are Epanechnikov with a 1.5 km bandwidth. Fire spread distances predictions were repeated 1,000 times for each fire in the sample.



Figures 2.7 and 2.8 illustrate the geographic distributions of net loss and net benefit fires, with unsuppressed fires causing structure losses at the observed sample loss rate and a rate of 1, respectively. The magnitudes of net losses and benefits are shown against the locations of major California cities, as well as wildland urban interface areas within California. In general, fires for which suppression generates net benefits appear to be more likely to be located closer to urban areas or extensive wildland urban interface areas. In contrast, fires for which suppression generates large net losses tend to be located in remote areas.

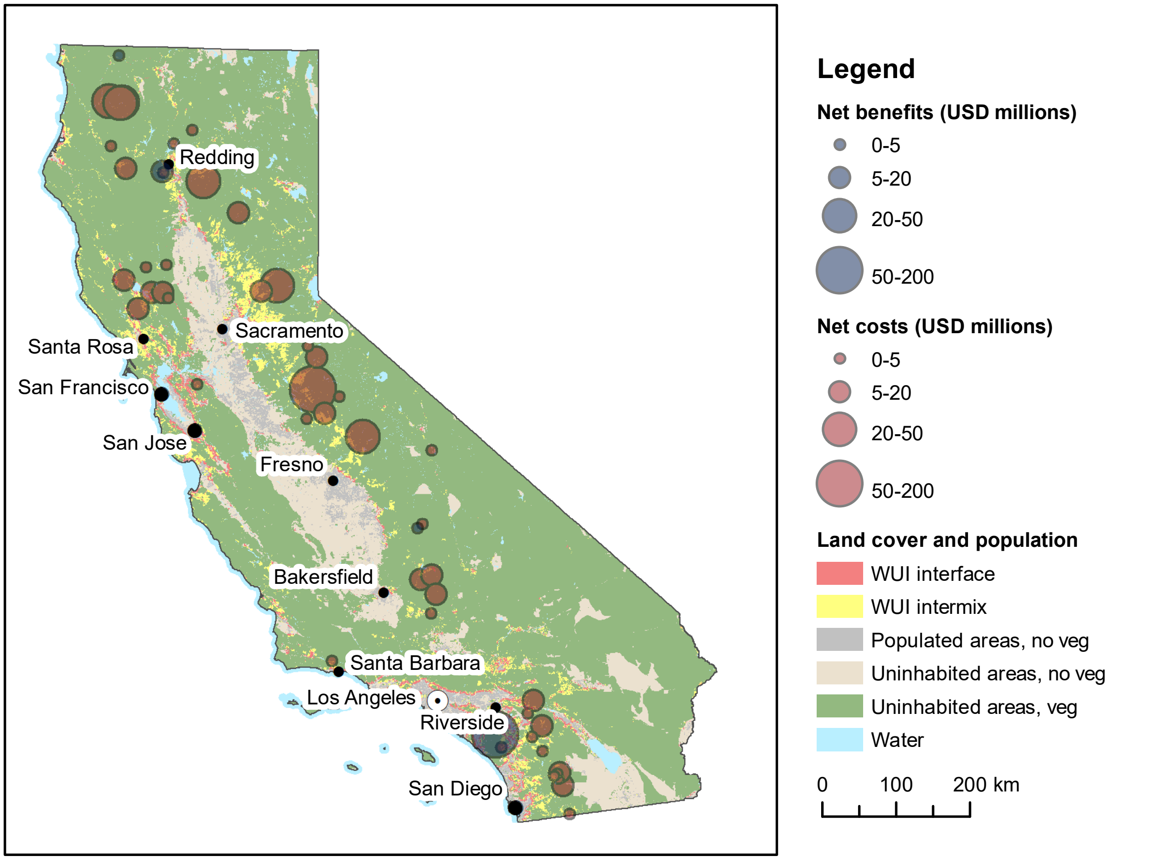
Figure 2.6: Distribution of net benefits and losses of fire suppression, estimated for the sample average loss rate and a loss rate of 1.



2.6 Discussion

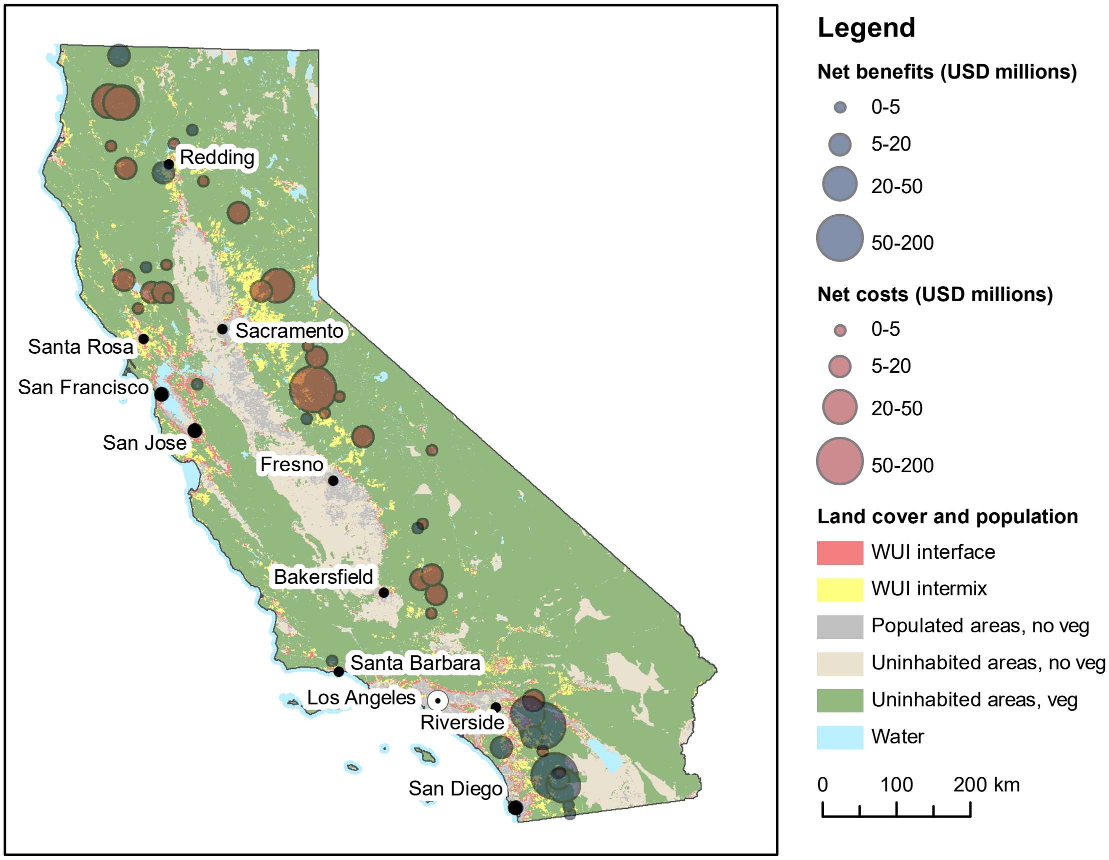
In this paper, I find that the net benefits of wildfire suppression, in terms of avoided losses to structures, vary widely across wildfires. While on some fires suppression is associated with very large net benefits, avoided losses to structures are not sufficient to justify suppression expenditure for many wildfires, especially those that begin in remote locations. This analysis is limited somewhat by the range of values for which I estimate benefits of suppression. I focus on avoided losses to structures, since protection of private property is a primary motivator of wildfire suppression effort (USDA OIG, 2017; Gude et al., 2013; Gorte, 2013). However, it is likely that the measure of structure value I use does not fully capture avoided private property losses due to suppression. In addition to damaging structures, wildfires can destroy their contents, as well as vehicles and other equipment stored on-site. Wildfire may also reduce the land value associated with a property due to reduced amenity values (Loomis, 2004; Stetler et al., 2010).

Figure 2.7: Geographic distribution of net benefits and net losses of fire suppresion, estimated using the sample average loss rate for unsuppressed fires



Furthermore, wildfire can have important effects on health outcomes and carbon emissions. Wildfire smoke has been shown to increase hospital emissions (Moeltner et al., 2013), as well as to have substantial negative consequences for labor supply (Borgschulte et al., 2016). Carbon effects may also be substantial. Over the past 10 years, fires have burnt on average 6.8 million acres within the U.S. each year (NIFC, 2016). Environment Canada estimates that wildfires within primarily coniferous ecosystems release 4.8 metric tons of carbon per acre burned. Using the EPA's current social cost of carbon of $36 per metric ton, this implies that costs of carbon released in U.S. wildfires is approximately

Figure 2.8: Geographic distribution of net benefits and net losses of fire suppresion, estimated using a loss rate of 1 for unsuppressed fires



$1.2 billion per year. If these additional benefits of wildfire suppression were included in the static analysis of costs and benefits of wildfire suppression in this paper, it is likely that suppression would be found to yield net benefits for a greater number of fires.

On the other hand, there is a large class of costs this paper excludes as well. While this paper treats the management of an individual wildfire as a spatial dynamic problem, it does not consider the effect wildfire management has on the management and outcomes of future wildfires. Although understanding benefits of wildfire suppression in a static setting is an important first step, the dynamic consequences of wildfire suppression are a significant omission that future work will need to address. Two dynamic consequences are particularly of note. First, government suppression of wildfire provides a subsidy to homeowners who choose to live in relatively risky locations. More aggressive wildfire suppression on behalf of homeowners increases this subsidy and should be expected to lead to increases in development within the wildland urban interface, thus increasing costs of suppression (Kousky et al., 2011). Second, fire serves a variety of important ecological roles, one of which is to remove burnable fuels that have accumulated over time. Though suppression can yield short-run benefits, when fire returns it may be likely to burn with greater intensity. Indeed, the increase in the frequency and severity of large wildfires within the western U.S. has been partially attributed to aggressive suppression over the course of the twentieth century (Arno et al., 1995; Schoennagel et al., 2004). Therefore, even when the short-run benefits of suppression outweigh its costs, an accounting that takes into consideration dynamic consequences may not favor suppression.

Moreover, this analysis measures the total benefits of suppression rather than its marginal benefits. While this is a limitation, the finding that total avoided losses to structures are in many cases lower than the total costs of suppression suggests that there may be many other fires for which marginal avoided losses are lower than marginal costs. My findings indicate that for some fires, we may be better off not suppressing rather than suppressing at our current level. However, if marginal costs of suppression are increasing and marginal benefits are decreasing, my results also suggest that we may be suppressing beyond the efficient level on a greater number of fires.

A possible explanation for these results is risk aversion on the part of wildfire managers. Previous research has indicated that fire managers may be excessively risk averse, and that this may affect their decision-making on wildfires (Wilson et al., 2011; Wibbenmeyer et al., 2013; Thompson, 2014). Figure 2.5 shows that in absence of suppression, most fires spread a relatively short distance; however, there is substantially more probability weight in the tail of the distribution of unsuppressed fire spread distances than there is for suppressed fires. While suppression costs outweigh expected benefits for many wildfires, fire managers may be averse to risking the possibility of a catastrophic outcome. Regardless of motivations, the results suggest that we may be over-allocating resources to suppression of some fires, especially remote wildfires. To be certain of this result, however, future research will need to investigate other benefits of fire suppression (such as avoided health costs), as well as the dynamic costs of wildfire suppression.

In addition to contributing to our understanding of responses to wildfire, this paper contributes to a very small literature on the benefits of adapting and responding to natural disasters. Previous work has indicated that adaptations and responses to other categories of natural disasters are possible, but they are taken up at relatively low levels, which indicates adaptation is expensive (Hsiang and Narita, 2012). Here, I find that mitigation responses, provided by government agencies, are adopted widely, but that in many cases the cost of responses may exceed their costs. As well, this paper contributes an empirical examination of management of a spatial-dynamic resource to a literature within which nearly all research has been theoretical in nature.

Table 2.2: Marginal effects of variables affecting suppression effort on probability of fire extinction

	(1)		(2)		(3)	
	Marg. Eff.	SE	Marg. Eff.	SE	Marg. Eff.	SE
Population density > 0						
m	-.011	(.013)	-.0049	(.014)	.033*	(.013)
$m+1$	.07**	(.012)	.066**	(.012)	.067**	(.011)
Total population						
m	8.3e-07	(.00024)	6.8e-06	(.00025)	.00019	(.00022)
$m+1$	.00046**	(.0001)	.00045**	(.0001)	.00044**	(.000099)
Total income						
m	-8.2e-09	(6.0e-09)	-8.7e-09	(6.1e-09)	-9.5e-09+	(5.6e-09)
$m+1$	-4.8e-09	(3.1e-09)	-4.5e-09	(3.0e-09)	-3.7e-09	(3.0e-09)
Per cap. income						
m	.00011	(.00066)	-4.7e-06	(.00067)	-.00043	(.00066)
$m+1$	-.00049	(.00055)	-.00033	(.00054)	-.00067	(.00054)
Contains major road						
m	.0028	(.015)	-.0011	(.015)	.038**	(.015)
$m+1$	.14**	(.012)	.14**	(.012)	.12**	(.012)
Area TES habitat (non-stream)						
m	.0015*	(.00064)	.0021**	(.00064)	.0017**	(.0006)
$m+1$	-.0019*	(.00076)	-.0024**	(.00077)	-.0025**	(.0007)
Area within 0.5 km of TES streams						
m	-.0003	(.00065)	-.00012	(.00066)	-5.7e-07	(.00062)
$m+1$	.0042**	(.00055)	.0043**	(.00058)	.0037**	(.00052)
Watershed imp. × area						
m	-.0028	(.0021)	.00079	(.002)	-.003	(.0023)
$m+1$	.0031	(.0028)	.00065	(.0027)	.0039	(.0028)
Cost variables						
TRI × area	-.0082**	(.00095)	-.0041**	(.0013)	-.00014	(.00094)
Area within 0.5 km of roads	.00051*	(.00023)	.0022**	(.00027)	.0029**	(.00025)
Fire spread controls	No		Yes		Yes	
Fire FE	No		No		Yes	
No. obs.	87,242		85,349		85,267	
No. fires	2,119		2,059		2,038	

Note: Three spatial leads were included for each variable. With few exceptions, second and third leads were not statistically different from zero, and they are omitted from the table. All models include distance from ignition fixed effects. Models two and three include cubic functions in simulated rate of spread and fire intensity, whose coefficients are reported in Table 2.3. All standard errors are clustered by fire. Symbols +,*, and ** denote statistical significance at the .1, .05, and .01 levels, respectively.

Table 2.3: Estimates of the effects of fire simulation outputs on extinction probability.

	(1)		(2)	
	Coef.	SE	Coef.	SE
Simulated rate of spread				
Linear	-.084**	(.03)	-.32**	(.04)
Quadratic	.0047	(.0047)	.03**	(.0063)
Cubic	-.00012	(.00019)	-.00096**	(.00028)
Simulated fire intensity				
Linear	.00057**	(.000096)	.0011**	(.00013)
Quadratic	-2.2e-07**	(3.7e-08)	-3.2e-07**	(5.1e-08)
Cubic	1.9e-11**	(3.1e-12)	2.4e-11**	(4.7e-12)
Fire spread controls	Yes		Yes	
Fire FE	No		Yes	
No. obs.	85,349		85,267	
No. fires	2,059		2,038	

Note: Columns 1 and 2 report fire spread coefficients from models estimated in columns 2 and 3 of Table 2.2, respectively. Both models include distance from ignition fixed effects. All standard errors are clustered by fire. Symbols +,*, and ** denote statistical significance at the .1, .05, and .01 levels, respectively.

Table 2.4: Estimates of the effects of demographic variables on extinction probability for models estimated with alternative link functions

	(1)		(2)		(3)	
	LPM		Logit		Probit	
	Marg. Eff.	SE	Marg. Eff.	SE	Marg. Eff.	SE
Population density > 0						
m	.023+	(.013)	.028*	(.013)	.026*	(.013)
$m+1$	.069**	(.011)	.068**	(.011)	.067**	(.011)
Total population						
m	.00021	(.00015)	.00015	(.00024)	.000081	(.00023)
$m+1$	.00031**	(.000067)	.00063**	(.00015)	.00057**	(.00013)
Total income						
m	-9.6e-09*	(4.0e-09)	-1.0e-08+	(5.9e-09)	-8.6e-09	(5.6e-09)
$m+1$	-5.6e-10	(2.1e-09)	-4.0e-09	(4.3e-09)	-4.4e-09	(3.7e-09)
Per cap. income						
m	-.000027	(.00059)	-.00024	(.00065)	-.00019	(.00063)
$m+1$	-.00069	(.00052)	-.00071	(.00054)	-.00065	(.00053)
Contains major road						
m	.036*	(.016)	.033*	(.015)	.033*	(.015)
$m+1$	.14**	(.013)	.13**	(.012)	.13**	(.012)
Area TES habitat (non-stream)						
m	.0013**	(.00048)	.0015**	(.00056)	.0013*	(.00054)
$m+1$	-.002**	(.00058)	-.0023**	(.00068)	-.0021**	(.00064)
Area within 0.5 km of TES streams						
m	.00014	(.00055)	.00012	(.00063)	.00022	(.00062)
$m+1$	.0033**	(.00058)	.0036**	(.00055)	.0034**	(.00056)
Watershed importance × area						
m	-.0033*	(.0016)	-.0033	(.002)	-.0033+	(.0019)
$m+1$	.0037+	(.0022)	.0041	(.0026)	.004	(.0024)
Cost variables						
TRI × area	-.00029	(.00073)	-.00022	(.00093)	-.0002	(.00077)
Area within 0.5 km of roads	.002**	(.0002)	.0025**	(.00024)	.0023**	(.00022)
Fire spread controls	Yes		Yes		Yes	
Fire FE	Yes		Yes		Yes	
No. obs.	85,345		85,267		85,267	
No. fires	2,055		2,038		2,038	

Note: All models include distance from ignition fixed effects and fire fixed effects, as well as a cubic functions in simulated rate of spread and simulated fire intensity. All standard errors are clustered by fire. Symbols +,*, and ** denote statistical significance at the .1, .05, and .01 levels, respectively.

Table 2.5: Marginal effects for demographic variables using alternative numbers of directions-of-spread for each fire

	(1) 48 directions		(2) 24 directions		(3) 6 directions	
	Marg. Eff.	SE	Marg. Eff.	SE	Marg. Eff.	SE
Population density > 0						
m	.022+	(.012)	.013	(.016)	.037+	(.022)
$m+1$	.084**	(.0097)	.07**	(.014)	.039+	(.022)
Total population						
m	-.000054	(.00037)	.000074	(.00016)	-.000061	(.000045)
$m+1$	.00047*	(.00021)	.00024*	(.000098)	.00012*	(.00006)
Total income						
m	-8.9e-09	(7.0e-09)	-2.5e-09	(4.7e-09)	4.6e-10	(1.6e-09)
$m+1$	1.1e-10	(6.4e-09)	-4.0e-09	(3.2e-09)	-2.0e-09	(2.0e-09)
Per cap. income						
m	.000021	(.0006)	.000098	(.00074)	-.00086	(.0011)
$m+1$	-.0011*	(.00047)	-.00074	(.00066)	.00004	(.0012)
Contains major road						
m	.065**	(.015)	.051**	(.017)	.02	(.019)
$m+1$	.13**	(.011)	.09**	(.016)	.08**	(.02)
Area TES habitat (non-stream)						
m	.003**	(.00095)	.00069	(.00043)	.00057+	(.00033)
$m+1$	-.0036**	(.0011)	-.00025	(.00057)	-.0003	(.00047)
Area within 0.5 km of TES streams						
m	-.0011	(.00097)	.00079+	(.00044)	.00034	(.00033)
$m+1$	.0069**	(.0008)	.0018**	(.0004)	.0009**	(.0003)
Watershed importance × area						
m	-.00089	(.0033)	-.00068	(.0016)	.0002	(.0011)
$m+1$	.00072	(.004)	.0022	(.0021)	-.00046	(.0017)
Cost variables						
TRI × area	-.00035	(.00089)	-.0012	(.00085)	-.00056	(.00036)
Area within 0.5 km of roads	.0051**	(.0004)	.0018**	(.0002)	.00084**	(.00013)
Fire spread controls	Yes		Yes		Yes	
Fire FE	Yes		Yes		Yes	
No. obs.	165,970		39,575		20,534	
No. fires	2,007		1,859		1,745	

Note: All models as specified in column 3 of Table 2.2. Standard errors are clustered by fire. Symbols +,*, and ** denote statistical significance at the .1, .05, and .01 levels, respectively.

Table 2.6: Net benefits of suppression for California fires 2012-2013, calculated under varying assumptions of the rate of structure loss in unsuppressed fires

	(1) $\mu^0 = 0.04$	(2) $\mu^0 = 0.5$	(3) $\mu^0 = 1$
Mean net benefit (USD millions)	-1.34	105.2	222.0
Median net benefit	-4.50	-1.54	-0.90
Minimum net benefit	-120.0	-32.7	-30.3
Maximum net benefit	247.1	2867.7	5740.3
Number of fires with net benefits ≥ 0	6	19	25
Number of fires with net benefits < 0	46	33	27

Note: For all columns, $\mu^1 = 0.04$.

Chapter 3

Salience and the Government Provision of Public Goods

Economists have identified many reasons why governments may fail to provide the socially optimal amount of public goods, including rent seeking (Gradstein, 1993), tax competition (Bucovetsky et al., 1998; Janeba and Wilson, 2011), political decision-making (Romer and Rosenthal, 1979; Barseghyan and Coate, 2014), and overlapping market areas (Hochman et al., 1995), among others. This paper examines another obstacle to efficient provision stemming from the government's reliance on the public to provide unbiased information about the benefits derived from public goods. To achieve the Samuelson (1954) condition, the government needs to know the demand for the good by each member of the public. The fact that government provision is required is an indication that markets for the public good are unlikely to exist, and thus that the government will not have market data at its disposal to determine preferences. An alternative is for the government to elicit preferences from the public. However, elicited preferences may not always reveal the true benefits from public goods. Samuelson recognized this problem, noting that "it is in the selfish interest of each person to give false signals, to pretend to have less interest in given collective consumption activities than he really has." Another source of "false signals" is that public preferences may be affected by behavioral biases.

We consider the case in which demands for public goods are distorted by salient events. Salience is a common behavioral bias whereby people's attention is drawn to salient features of a decision problem, leading them to overweight prominent information in subsequent judgments (Taylor and Thompson, 1982). Empirical evidence from economics shows that salience affects human decision-making in a broad range of situations. Consumers are found to be less responsive to changes in price if those prices occur through increased shipping and handling charges (Hossain and Morgan, 2006) and stock prices are less responsive to earnings reports when they are issued on Fridays, when investors are likely to be less attentive (DellaVigna and Pollet, 2009). Consumers are more responsive to tax changes when they are more openly exhibited (eg. Finkelstein, 2009; Chetty et al., 2009; Cabral and Hoxby, 2012). Sexton (2015) found evidence that when utility customers are enrolled in an automatic bill-pay program, which lowers price salience, they are more likely to consume greater amounts of energy.

Salient events can bias the preferences expressed by the public, resulting in the inefficient provision of public goods. As an illustration of this idea, consider the government's response to terrorism. Terrorist attacks raise fears among the public about the reoccurrence of attacks and have often been followed by military operations and government investment in security. Viewed through the lens of salience, one can think of an attack as focusing the public's attention on the losses that would be incurred under a future attack. To the extent that these losses stand out from payoffs in other states of the world, the public may overstate the expected benefits of government actions to reduce threats of future attacks. One can envision a similar mechanism at work with government provision of public goods following natural disasters, disease outbreaks, and environmental catastrophes.

We formalize the notion of salience in a simple model of public good provision. In our model, the government allocates a local public good to a community based on expected benefits elicited from the residents.[1] The benefits are expressed as a two-state lottery, and we assume that one of the payoffs is altered by an exogenous shock. Applying the mechanism in Bordalo et al. (2012b), the change in the payoff raises its salience and results in a re-weighting of the state probabilities. This affects the expected benefits from the public good and the amount allocated by the government. The theoretical model is used to derive two results. First, we find the conditions under which allocation of the public good increases or decreases following the shock. An important insight for the empirical analysis that follows is that even if the shock lowers the payoff, expected benefits and the public good allocation can increase. Second, we show that in general the government allocation will be inefficient.

We estimate the effects of salience on public good provision with an empirical analysis of government projects to reduce wildfire severity. Federal agencies in the U.S., including the U.S. Forest Service, manage 250 million hectares of wildlands. A central activity for these agencies is controlling wildfire, on which they spend approximately \$3 billion annually (Gorte, 2013). Of this amount, roughly \$0.5 billion is allocated to pre-fire fuels management projects, which involve removing fuels from the landscape through mechanical thinning and controlled burns. The goal of these projects is to reduce the severity of wildfires when they occur.[2] We analyze whether projects are more likely to be placed near communities that have experienced a recent wildfire. Because fire is a

[1]In practice, preference elicitation can take several forms. The government may use survey methods, such as contingent valuation (Mitchell and Carson, 1989), or preferences may be revealed by behavior in related markets and recoverable by hedonic price or travel costs methods (e.g., Freeman et al. (1993)). Alternatively, the government may elicit preferences through such means as public hearings or contacts with citizens and elected officials, or from voting results (Osborne and Turner, 2010). Our theoretical results are also robust to the possibility that government officials themselves are affected by salience.

[2]For example, removing understory vegetation can reduce the likelihood that trees will burn in a fire. By reducing the severity of the fire, the agency can lower suppression costs and property damage.

contagion process whose spread depends on fuel availability, wildfires have the same effect as fuels management projects — namely, they reduce the volume of fuels and thus the severity of future fires in an area. Yet, despite the fact that wildfires reduce fire risk, our theory suggests that salient wildfires may lead the public to overstate the benefits of fuels management projects. This may result in public agencies locating projects close to communities that have lower risk because of recent close wildfires.

We identify the effects of salience with a rich panel data set on all fuels management projects on federal forest lands in the western U.S. between 2003 and 2011. The dependent variable in our empirical model is a binary indicator for whether a fuels management project was implemented on a given plot of land (cell i) in year t. We focus on cells that are close to wildland-adjacent communities, which are potentially vulnerable to damages from wildfire. We think of wildland-adjacent communities as being "treated" when a wildfire occurs close by and test how treatment changes the probability of fuels management near the treated community. We measure effects in the year of the fire and for several years following the fire. Our specification includes grid cell fixed effects to control for time-invariant determinants of fuels management decisions, such as fire hazard and proximity to assets at risk,[3] and year-by-region fixed effects to control for time-trending unobservables, such as changes in fuel moisture content. We find strong evidence that fuels management projects are more likely to be placed near treated wildland-adjacent communities. Our main results are robust to different definitions of "close" fires and projects, alternative ways of clustering standard errors, corrections for serial correlation, inclusion of placebo one and two year leads, and changes in the sample.

An alternative explanation for our empirical results is that government agencies use the occurrence of wildfires to learn about risks from future fires, as in the application to

[3]Fire hazard refers to the conditions on the landscape that affect fire behavior, including vegetation type and terrain. Fire risk is the probability that natural resources, structures, etc., are destroyed by wildfire.

flooding by Gallagher (2014). We use two approaches to rule out learning as a competing explanation for our results. First, the fixed effects in our model control for all time-invariant and region-level time-varying determinants of fire risk. The regions are defined as sufficiently small areas (e.g., ranger districts) so that there should be little within-region variation in fire risk trends. Second, we incorporate into the model a time-varying measure of vegetation condition that indicates potential wildfire severity. We show that the effect of a nearby fire on the likelihood of a fuels management project does not vary with the vegetation condition, as would be expected if the fire informed managers about the risk of future fires. In addition, we provide further support for the salience mechanism by showing that effects of close wildfires are magnified near communities with greater population and more housing units. Consistent with salience theory, our tests show that close wildfires treat the residents of wildland-adjacent communities and that fuels management decisions depend on the risks perceived by these residents rather than objective risks.

In the next section, we present the theoretical model. Section 3 describes the data used in our empirical study, and section 4 presents the main empirical specification and results, followed by a series of sensitivity analyses, robustness checks, and evaluation of learning as an alternative to salience. Conclusions are in the final section.

3.1 Theory

Our model builds on recent papers by Bordalo, Gennaioli, & Shleifer who provide a formal model of the effects of salience on individual decision making. In their work, salience is represented by a function that compares each attribute of a good to a reference level in order to determine how much that attribute "stands out". A salience parameter determines the degree to which the salient attribute is weighted in determining the consumer's valuation of the good. This model is used to explain commonly observed behavioral biases such as context-dependent willingness-to-pay (Bordalo et al., 2013) and endowment effects (Bordalo et al., 2012a). Our analysis draws, in particular, on Bordalo et al. (2012b), who apply salience theory to choice under risk. The authors use their model to explain long-observed behavioral anomalies such as the Allais paradox and preference reversals, to account for risk-averse and risk-seeking behavior by the same individual, and to explain under- and over-weighting of highly unlikely events. Our paper extends the work of Bordalo, Gennaioli, & Shleifer, which focuses on individual decision-making with respect to private goods, to public goods where government provision is required.

The decision-maker in our model is a government agency that provides a local public good to a community of N residents. The cost of allocating Q units of the good is $C(Q)$, where $C' > 0$, $C'' > 0$. The public good provides constant marginal benefits b to individuals within the community. Thus, total benefits from Q units of the public good are $B(Q) = NbQ$. The marginal benefit b is a random variable whose value depends on the future state of the world. We assume there are two states, denoted $i = \{1, 2\}$, and define b_i as the marginal benefit in state i. The states of the world occur with probability $\pi_i > 0$, and thus the benefits from the public good can be represented by the lottery $\{(\pi_1, b_1), (\pi_2, b_2)\}$, where $\pi_2 = 1 - \pi_1$. The lottery's payoffs are assumed to be private information known only by the community's residents. We discuss, below, the extension of the model to the case where government officials are affected by salient events.

There are two time periods. At the start of each period, the agency elicits preferences for the public good from residents of the community[4] and allocates the good to maximize expected net benefits. We allow for residents to be "local thinkers" in the terminology

[4]Our model accommodates other means by which the government learns about preferences. Residents may express their demands directly to the agency or indirectly through elected officials and voting.

of Bordalo et al. (2012b), meaning they overweight salient payoffs in determining the expected value of the public good. As the government agency must rely on the revealed or stated preferences of the residents, the agency's estimate of the expected benefits from the public good embeds the effects of salience.[5] Therefore, the agency allocates Q units of the public good such that $C'(Q) = N\tilde{E}(b)$, where $\tilde{E}(b)$ represents the expected value of b as expressed by residents of the community. In results presented below, we contrast the public good allocation based on $\tilde{E}(b)$ with the allocation that uses $E^*(b) = \pi_1 b_1 + \pi_2 b_2$, which is computed with the objective probabilities π_1 and π_2.

Bordalo et al. (2012b) model the psychological effects of salience in three stages. First, decision-makers rank the salience of possible states of the world according to a salience function. Importantly, the salience function has the *ordering* property: the salience of a state is increasing in the distance between the payoffs across lotteries. Second, based on the salience-rank $k_i \in \{1, 2, ...\}$ of state i, where lower integers indicate more salient states, the probability of state i is distorted to $\tilde{\pi}_i = \omega_i \pi_i$, where:

$$\omega_i = \frac{\delta^{k_i}}{\sum_i \delta^{k_i} \pi_i}. \tag{3.1}$$

The parameter $\delta \in (0, 1]$ captures the degree to which salience distorts the decision weights. When $\delta = 1$, $\omega_i = 1$ for all i and there is no distortion of the objective probabilities. As δ tends toward zero, the decision-maker places more and more weight on a lottery's most salient payoffs. Third, decision-makers choose among lotteries according to their expected values calculated with the weighted probabilities $\tilde{\pi}_i$.[6]

[5] In particular, because payoffs are private information, the government cannot distinguish over-weighting of salient payoffs from changes in payoffs.

[6] As an example, consider the pair of lotteries, $\{(0.5, -1000), (0.5, 1000)\}, \{(0.5, 0), (0.5, 1000)\}$. The local thinker will tend to ignore the upside payoff (1000) because it is the same in both lotteries. Instead, she will focus on the downside payoffs, consistent with the ordering property, and re-weight the probabilities according to equation 3.1. In the case where $\delta = 0.5$, the expected values of the lotteries (0 and 500) become -333 and 333, respectively.

In our two-period model, we assume that the payoffs from the public good change as the result of an exogenous shock occurring between periods 1 and 2. In general, the shock could change either or both of the payoffs b_i. However, for simplicity and because it is consistent with our empirical application, we consider a change only in the state 1 payoff: payoff b_1 changes to b_1' in period 2, while b_2 is the same in both periods. By the ordering property of the salience function, state 1 is more salient than state 2 because the shock produces a non-zero difference in the state 1 payoff between periods 1 and 2. Thus, the salience ranking for the time 2 lottery is $(k_1, k_2) = (1, 2)$. The weighting functions for state probabilities are then given by:

$$\omega_1 = \frac{\delta}{\delta\pi_1 + \delta^2\pi_2}, \omega_2 = \frac{\delta^2}{\delta\pi_1 + \delta^2\pi_2} \tag{3.2}$$

It follows that when $\delta < 1$, $\omega_1 > 1$ and $\omega_2 < 1$ and, thus, $\tilde{\pi}_1 > \pi_1$ and $\tilde{\pi}_2 < \pi_2$. The shock to payoffs leads to an over-weighting of the payoff in the salient state.

We use the model to derive two results. The first considers whether the shock increases or decreases the provision of the public good to the community. The second result examines whether the allocation of the public good is efficient. To derive the first result, we assume that the period 1 provision of the public good is based on the expected value $E^*(b)$, derived with the objective probabilities π_1 and π_2. This assumption is not essential, as we could allow for these probabilities to depart from their true values as a result of earlier salience effects. What is critical for this result is just that the shock distorts the period 1 probabilities. However, for the second result it is essential that we use $E^*(b)$ to determine the efficient allocation of the public good.

Result 1. If $b_2 - b_1 > 0$, the agency will increase (decrease) the provision of the public good when $\delta > m$ ($\delta < m$). If $b_2 - b_1 < 0$, the agency will increase (decrease) the provision of the public good when $\delta < m$ ($\delta > m$), where:

$$m = \frac{\pi_2(b_2 - b_1) - (b_1' - b_1)}{\pi_2(b_2 - b_1)}$$

Proof. A proof is provided for the case $b_2 - b_1 > 0$. An parallel argument is used for $b_2 - b_1 < 0$. According to the agency's allocation rule, the amount of the public good provided is increasing in its expected value. Therefore, the amount provided will increase (decrease) if $\tilde{E}(b) > E^*(b)$ ($\tilde{E}(b) < E^*(b)$). Express the inequalities as $\tilde{\pi}_1 b_1' + \tilde{\pi}_2 b_2 \gtrless \pi_1 b_1 + \pi_2 b_2$ and rearrange to obtain $(1-\tilde{\pi}_2)(b_1' - b_1) \gtrless (\pi_2 - \tilde{\pi}_2)(b_2 - b_1)$, using $\tilde{\pi}_1 = 1 - \tilde{\pi}_2$ and $\tilde{\pi}_1 - \pi_1 = \pi_2 - \tilde{\pi}_2$. Substitute for $\tilde{\pi}_2$ and rearrange to obtain $\delta > m$ ($\delta < m$). □

We highlight a result for the case $b_2 - b_1 < 0$ that matches our empirical application to wildfire. The state 1 payoff b_1 corresponds to the benefits of fuels reduction when a wildfire occurs, which naturally are larger than the benefits when a fire does not occur (b_2). The shock is a wildfire between periods 1 and 2, which reduces the losses under a future fire by removing fuels from the landscape and decreasing fire severity. This reduces the marginal benefits of fuels reduction projects when a fire occurs ($b_1' < b_1$). However, it also increases the salience of the state 1 payoff. If the salience effect is strong enough (δ is sufficiently small), then enough weight can be shifted to the higher state 1 payoff to raise the public's expected value for fuels management.[7] Thus, we might find an increase in the allocation of fuels management following a fire ($\delta < m$), even though the true expected value of fuels reduction projects has declined.

Result 2. Salience leads to an inefficient allocation of the public good except when $b_1' = b_2$ or $\delta = 1$.

Proof. Given the change to payoff 1, the efficient allocation of the public good should be

[7] For this to happen, the decline in the state 1 payoff $(b_1 - b_1')$ cannot be too large, implying $0 < m < 1$.

based on the expected benefit $E^*(b) = \pi_1 b'_1 + \pi_2 b_2$. However, the agency will elicit the value $\tilde{E}(b)$ from residents of community, resulting in an over- or under-allocation of the good as $\tilde{E}(b) \neq E^*(b)$. It is easily be shown that $\tilde{E}(b) = E^*(b)$ only when $b'_1 = b_2$ or when $\tilde{\pi}_1 = \pi_1$ (which implies $\tilde{\pi}_2 = \pi_2$). The latter condition obtains only when $\delta = 1$. $\square$

When the salience parameter equals 1 or the payoffs in the two states are the same, the probability weights do not affect the allocation decision. Otherwise, when $b'_1 < b_2$, a larger weight will be put on the smaller payoff (b'_1), resulting a smaller expected value and an under-allocation of the public good. The opposite result obtains when $b'_1 > b_2$.

Our theory assumes that the preferences of residents are distorted by salient events. Another possibility is that government officials themselves are influenced by salience. In this case, if the government's objective is still to maximize expected net benefits derived by local residents, then the results of our model carry through.[8] Similar to the example discussed above, a salient wildfire can lead the government to over-estimate the expected benefit of allocating fuels management projects in an area that just experienced a wildfire. Whether salient events affect residents or government officials, a testable implication of our theory is that salience effects will vary with characteristics of the communities receiving the public good.[9] This result is confirmed in our empirical analysis, revealing that residents of wildland-adjacent communities are part of the mechanism by which salient events affect the allocation of fuels management projects.

[8] Anderson et al. (2013) find that public forest managers balance public responsiveness with technical management.

[9] A salient event alters the expected benefits $E(b)$. Applying the Implicit Function Theorem to the first-order condition $C'(Q) = NE(b)$ yields $\frac{dQ}{dE(b)} = \frac{N}{C''} > 0$. This result shows that the salience effect depends on the population size of the community.

3.2 Data

To test the effects of salience on the provision of local public goods, we combine an extensive panel data set of the locations of fuels management projects on public lands with spatial data on wildfire perimeters and locations of wildland-adjacent communities. Due to the importance of wildfire management in the western U.S., we focus our attention on lands in 15 western states[10] managed by the U.S. Forest Service (USFS), Bureau of Land Management (BLM), and National Park Service (NPS). We identified these public lands using BLM and NPS boundaries (BLM, 2014) and administrative National Forest boundaries for USFS lands. Combined, our study area encompasses approximately 1.5 million square kilometers of federal land, of which the USFS and BLM manage roughly equal shares (47%), with the remaining 6% is managed by the NPS. We divided this area into a grid of 1 km $\times$ 1 km cells, since this is the approximate size of the average fuels management project in our data. These 1 km^2 cells are the units of analysis for the empirical analysis.

The fuels management data come from the National Fire Plan Operations and Reporting System (NFPORS). The NFPORS database records the point location (latitude and longitude), dates, and area of all fuels reduction projects for USFS and the Department of Interior (including BLM and NPS) lands in the years 2003-2011. Projects are classified as controlled burns, mechanical thinning, preparation for treatment, and other. Controlled burns and mechanical thinning account for 94% of the observed projects in our data. Because NFPORS does not provide the boundaries of fuels management projects, we used the reported point location and area to estimate boundaries. Using ArcGIS, we created a polygon layer in which fuels management projects were represented by circles of the reported area, centered on the reported point location. A grid cell was designated

[10] These states are Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oregon, South Dakota, Utah, Washington, and Wyoming.

as having received fuels reduction in a given year if the grid cell's centroid was inside of an imputed project boundary in that year.

Although the majority of land under federal management is forested (52%), there are significant areas in shrubs (39%) and grasslands (7%).[11] Our data reveal that fuels reduction projects are implemented on non-forest lands, but at a much lower rate than on forest lands. As shown in the first panel, second column of Table 3.2, for the whole sample the rate of fuels reduction projects in evergreen or mixed forests is 2.5%. The rate is lower (1.1%) in deciduous forests, but still much higher than for other land cover types. Since fuels reduction activities are concentrated in evergreen and mixed forests, and the relationships between fire events, fuels reduction activities, and future fire risk are much less clear in deciduous forests and other land cover types (Keeley et al., 2009; Moritz et al., 2014), we focus our attention hereafter on forest (evergreen and mixed forests) lands.[12] For the forest-only sample, the USFS is the dominant land management agency (83% of all grid cells), followed by the BLM (13%) and the NPS (4%).

We define wildland-adjacent communities as wildland urban interface (WUI) Census blocks, which encompass both interface, where developed residential areas directly abut large areas of wildland vegetation, and intermix, where residences are dispersed among wildland vegetation (USDA & DOI, 2001). Wildland urban interface data come from Radeloff et al. (2005), who mapped U.S. WUI areas using landcover and housing density data. For our purposes, we consider as WUI any U.S. Census block within our study region that Radeloff et al. (2005) classified as low, medium, or high density interface or intermix in 2000. Descriptive statistics for all WUI blocks in the study region are provided in the second column of Table 3.2.

[11] We obtained these estimates by overlaying the National Land Cover Data for 2006 on the federal agency data described above.

[12] In results not reported here, we find evidence of salience effects on non-forest lands, although it is less conclusive.

Table 3.1: Rates of fuels management projects by land cover type

	Rate of fuels management		Fuels management projects per grid cell				
	Mean	No. obs. (grid cell-years)	None	Once	Twice	3 or more times	No. obs. (grid cells)
I. All grid cells							
Evergreen or mixed forest	0.025	4,830,399	0.86	0.089	0.030	0.020	536,711
Deciduous forest	0.011	211,077	0.93	0.052	0.013	0.005	23,453
Shrubland	0.005	6,392,430	0.97	0.022	0.006	0.003	710,270
Herbaceous	0.006	1,105,470	0.96	0.025	0.007	0.005	122,830
Other	0.005	472,635	0.98	0.015	0.005	0.004	52,515
Total	0.013	13,012,011	0.93	0.047	0.015	0.010	1,445,779
II. Grid cells $<$ 5 km from WUI							
Evergreen or mixed forest	0.035	1,864,575	0.82	0.108	0.041	0.033	207,175
Deciduous forest	0.012	98,073	0.92	0.057	0.014	0.006	10,897
Shrubland	0.010	1,450,062	0.95	0.035	0.011	0.008	161,118
Herbaceous	0.011	246,996	0.94	0.038	0.012	0.009	27,444
Other	0.012	103,482	0.94	0.037	0.013	0.011	11,498
Total	0.022	3,763,188	0.88	0.072	0.026	0.020	418,132

Note: Land categories taken from the 2006 National Land Cover Database (Fry et al., 2011). Evergreen forests and deciduous forests consist of greater than 75% evergreen and deciduous trees, respectively. Mixed forests are areas where neither evergreen nor deciduous tree species dominate. Shrubland is areas dominated by shrubs less than 5 meters tall. Herbaceous land includes land dominated by grasses or other herbaceous vegetation. Other includes planted or cultivated land, developed land, wetlands, barren areas, and water. For example, on evergreen and mixed forests, 2.5% of our grid cell-year observations are treated (our dependent variable equals 1 2.5% of the time). 86% of evergreen or mixed forest grid cells in the study area never received a fuels reduction treatment. 2.0% of grid cells were treated 3 or more times. Out of the 1,445,779 grid cells, 536,711 are mixed forest or evergreen forest.

Fire data come from the interdepartmental Monitoring Trends in Burn Severity (MTBS) project (Eidenshink et al., 2007). In the western U.S., MTBS uses Landsat satellite imagery to map fire perimeters for fires larger than 1000 acres (approximately 4

Table 3.2: Descriptive statistics for WUI block data set

	All obs. (mean)	Obs. within 5 km threshold (mean)
Distance to nearest fire in study period (km)	15.4	14
Population*	4,948	4,660
No. of housing units*	2,197	2,460
Per capita income*	21,361	21,182
Percent graduated high school*	83.8	86.5
Number of observations	454,767	105,613

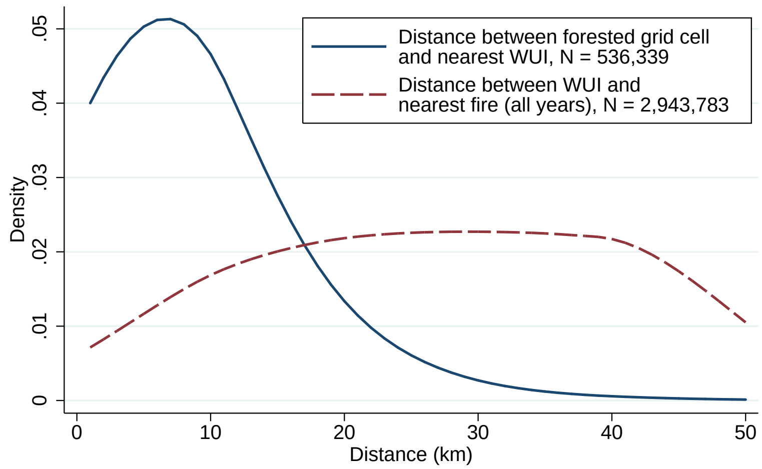
*Variable is observed only at the Census tract level.

km^2). This focus on larger fires makes sense for this study, since we expect larger fires to be most salient to the public.

Our analysis relies on two distance measures: the distance between each forested grid cell and its nearest WUI blocks and the distance between each WUI block and the nearest fire. For each cell, we calculated the straight-line distance to up to 500 of the nearest WUI blocks within a threshold distance of 10 km. Among the nearly 1.5 million grid cells in our sample, only 3,147 were matched with the maximum number of WUI blocks. Therefore, limiting the sample to the closest 500 WUI blocks is unlikely to influence our results. In a similar way, we measured the straight-line distance from each WUI block to the nearest fire in each year. Figure 3.1 provides the kernel density functions for our two distance measures. For forested cells, distances of less than 13 km to the nearest WUI block are the most common. The density for distances between WUI blocks and the nearest fire is roughly uniform, although the likelihood of fires within 15 km or more than 40 km is somewhat lower.

Our empirical strategy requires dropping grid cells that are not close to at least one WUI block, since we expect the placement of fuels reduction activities far from human settlement to be determined by factors other than the salience of wildfire risk (e.g., protection of timber resources). In our main set of results, the sample consists only of

Figure 3.1: Kernel density plots of the distributions of distance to WUI and distance to nearest fire within the sample of forested grid cells and WUI blocks, respectively



Note: Epanechnikov kernel density functions with bandwidth 5. Distributions are across observations for which the target layer is closer than 50 kilometers. There are 372 grid cells for which the nearest WUI block is further than 50 km. There are 4,787,256 WUI block−years for which the nearest fire is further than 50 km.

grid cells closer than 5 km from the nearest WUI block. As described below, however, we test the sensitivity of our results to different definitions of closeness to WUI blocks. We find that restricting our attention to grid cells near WUI blocks has little effect on the basic characteristics of our sample. Compared to the whole sample of grid cells, the rate of fuels reduction projects increases somewhat when we consider only grid cells within 5 km of a WUI block, but the rate is still highest on forest lands (Table 3.2, panel II). Restricting our attention to grid cells within 5 km of a WUI reduces the number of WUI blocks by 77%, but has little effect on average community characteristics (Table 3.2).

To test whether learning can explain our results, we use a measure of vegetation condition from the Landfire project.[13] The Vegetation Condition Class (VCC) is a cardinal measure of the degree to which the current vegetation departs from simulated historical vegetation conditions. For example, the largest value of VCC corresponds to “high

[13]Landfire is a partnership of U.S. land management agencies to provide geospatial data on vegetation, wildland fuel, and fire regimes. See https://www.landfire.gov/about.php#planning (accessed August 31, 2017).

departure", which is indicative of a landscape on which fuels have built up due to long-term fire suppression. A fine-scale measure of the VCC is available for 2001, 2008, and 2012, which we match to the grid cell data described above. Further tests are conducted with measures of population and number of housing units (Table 3.2). Because access to block-level U.S. Census data is restricted, these variables are measured at the Census tract level using data from the 2000 Census.

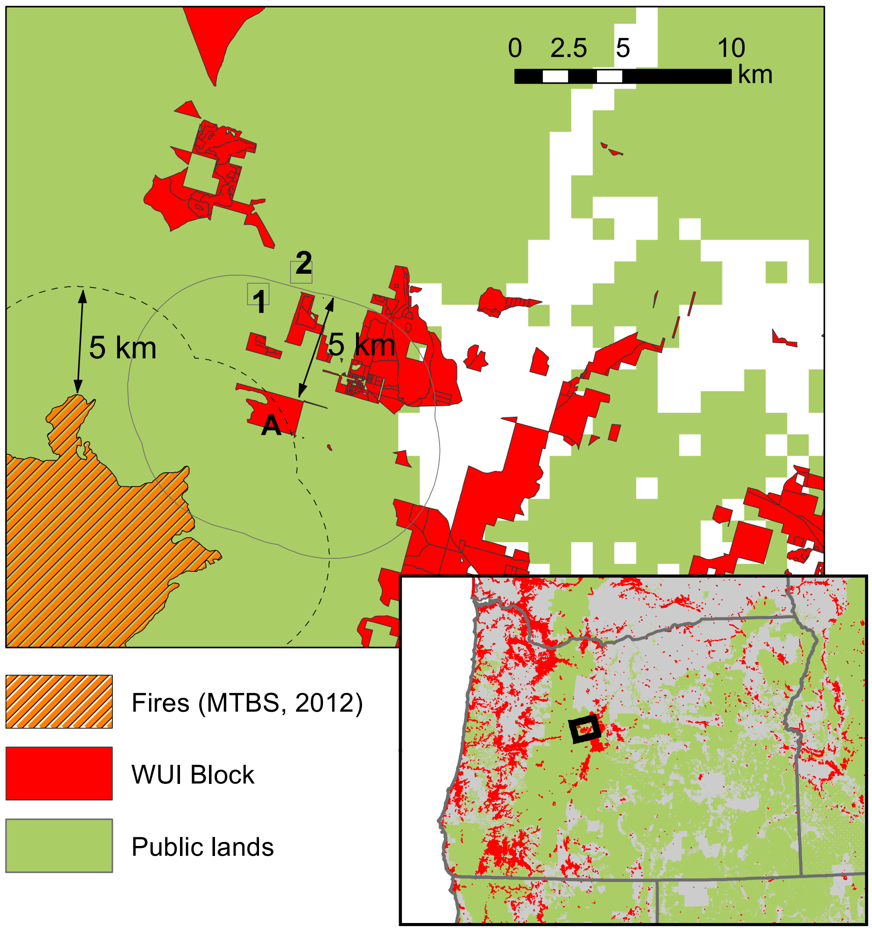
3.3 Empirical model & results

3.3.1 Overview

The essence of our empirical approach is to determine whether fuels management projects are more likely to occur on federal lands that are close to WUI communities that have experienced nearby wildfires. We expect wildfire risk to be more salient to WUI residents if they can observe smoke plumes, fire-fighting efforts, and possibly the fire itself. Such highly localized effects of wildfires are supported by findings in McCoy and Walsh (2014) that fires influence housing prices only if they are within 5 km.

We motivate our empirical approach with Figure 3.2, which shows a small portion of our study area in the State of Oregon. Light-shaded areas depict lands managed by federal agencies, and dark-shaded areas are Census blocks classified as WUI. The hatched area is the burn scar from a fire that occurred in 2011. We think of WUI blocks as being "treated" by close fires in the sense that the fire raises the salience of wildfire risk for residents of the WUI block. Our definition of close is varied in the empirical analysis, but for this illustration it is defined as 5 km. As such, WUI block A is treated because it is within 5 km of the fire, but WUI blocks farther than 5 km from the fire are untreated. We then consider whether there is a higher probability of fuels reduction projects occurring

Figure 3.2: Illustration of the experimental design



in close proximity to the treated WUI block. We identify all grid cells on federal lands that are within 5 km of some portion of a WUI block. Grid cells 1 and 2 meet this criterion (the radius of the solid circle is 5 km). However, only grid cell 1 is close (within 5 km) to at least one treated WUI block (WUI block A), whereas grid cell 2 is close to untreated blocks. We test whether grid cells that are close to WUI blocks that are close to fires (e.g., cell 1) are more likely to receive a fuels management project than grid cells that are close to WUI blocks that have not experienced a nearby fire (e.g., cell 2).

In place of distance to an event, some recent studies have measured salience using more direct measures of information transmission. Gallagher (2014) uses the number of local television stories on floods as a measure of media exposure. For our application, however, media markets are large relative to the scale at which we expect the effects of wildfires to operate. In the western U.S., local television media markets are comprised of many counties and, in some cases, large portions of states.[14] Furthermore, to identify effects of media coverage we would need to omit year-by-region fixed effects from our model that are defined at much smaller scales than media markets. A second possible way to operationalize salience is by whether the fire is visible, since McCoy and Walsh (2014) find that a wildfire has a larger effect on housing prices if the burn scar is visible from a house. Measuring the visible features of a wildfire is difficult in our case because we are interested in effects on communities of people rather than single points in space. Communities are delineated with Census blocks, which are often large in the low density WUI areas we study. Because of the limitations of media markets or visibility in this context, we use distance to operationalize salience. We present tests, below, that strengthen our case for using distance to measure the degree of risk salience.

3.3.2 Main specification

As in recent applications of the difference-in-differences estimator (eg. Conley and Taber, 2011; Abrevaya and Hamermesh, 2012), we estimate our main specification using a linear probability model. In a panel data setting, the advantage of the linear probability model is the ease of including fixed effects. In our application, fixed effects play a critical role in controlling for unobserved determinants of fuels reduction activities, such as underlying fire hazard and proximity to assets at risk. An alternative is a binary probit or logit specification. However, including fixed effects in these models gives rise to the incidental parameters problem that renders maximum likelihood estimates inconsistent.

[14] See `http://www.nielsen.com/intl-campaigns/us/dma-maps.html` (accessed August 31, 2017).

The linear probability model is a good alternative considering that all of our regressors are dummy variables and our goal is to estimate their effects at the mean of the data (Wooldridge 2010).

The main specification of the linear probability model is:

$$y_{it} = \alpha_i + \sum_{\ell=-4}^{0} \beta^{\ell} \mathbb{1}\{\exists s \in S_i : firedist_{s,t+\ell} \leq c\} + \delta_{tm(i)} + \epsilon_{it} \tag{3.3}$$

where i, t, and s, index cells, years, and WUI blocks, respectively, and $m(i)$ is a mapping from cell i to an aggregate geographical region (e.g., a Census tract), indexed by m. The dependent variable, y_{it}, equals 1 if a fuels management project occurs on cell i in year t and is 0 otherwise. $S_i = \{s : wuidist_s \leq d\}$ where $wuidist_s$ is the distance from cell i to WUI block s and d is a threshold value. Thus, S_i is the set of all WUI blocks within distance d of cell i. The indicator function $\mathbb{1}\{\cdot\}$ equals one when a fire occurs close to at least one of the WUI blocks in the set S_i. Specifically, $firedist_{s,t+\ell}$ is defined as the distance to the closest fire to WUI block s that occurs in year $t+\ell$. If that fire is within distance c of WUI block s and block s is in the set S_i, then the indicator function equals one. The parameters of the model are α_i, β^{ℓ}, and $\delta_{tm(i)}$, and ϵ_{it} is a random disturbance term. The summation term in equation (3.3) allows each fire to have a contemporaneous effect on the probability of fuels management projects ($\ell = 0$) and four annual lagged effects ($\ell =$ -1 to -4). We examined specifications with more lags, but did not find any significant coefficients outside the range of effects in equation (3.3).

We identify the salience effects of wildfire based on within grid cell and within year-by-region variation. We would expect decisions about fuels management projects to be influenced by such factors as fire hazard, access, and administrative unit. We implicitly control for these time-invariant factors with cell-level fixed effects α_i.[15] Time-varying

[15]With fixed effects included, cells that are never included in fuels management projects have no

factors could include macroeconomic trends affecting government budgets, fluctuations in weather, and changes in management objectives. We control for these factors with year-by-region effects $\delta_{tm(i)}$ where regions are alternatively defined as units (USFS national forests, BLM district offices, NPS national parks), districts (USFS ranger districts, BLM field offices), counties, and Census tracts. Districts are less aggregated than units[16] and Census tracts are less aggregated than counties. These regions are sufficiently small areas so that within-region variation in fire risk trends should be minimal.[17] We also consider the degenerate case of a single region, which amounts to including year effects.

We are concerned about the possibility of spatial autocorrelation, which can bias estimates of standard errors. If, for example, fuels reductions span more than one grid cell, then the fuels reduction status of neighboring grid cells may be correlated. To account for this possibility, we cluster the residuals in two ways, first at the district level and next at the unit level. As a check of robustness, we also estimated our main specifications with clustering at the level of Census tracts and counties. Our choice of geographic unit on which to cluster does not substantively affect our results.

The results for the main specification are reported in Table 3.3. All model versions include cell fixed effects (α_i) and consider pixels and wildfires within 5 km of WUI blocks (i.e., $c = d = 5km$). The models vary according to the type of year-by-region fixed effects included. Model (1) includes only year effects. We find the contemporaneous effect of a close wildfire on the probability of a fuels reduction project to be 1.6 percentage points, an estimate that is significantly different from zero at the 1% confidence level. We interpret the contemporaneous effect as an immediate response to a wildfire.[18] The effect is large

influence on the model estimates.

[16]For NPS lands, there is no region less aggregated than a unit (National Park); therefore, year-by-district fixed effects and year-by-unit fixed effects are equivalent on NPS lands.

[17]We discuss potential time-varying determinants of fire risk in more detail, below, when we evaluate learning as an alternative explanation for our results.

[18]Alternatively, fuels reduction projects could be accurately placed in anticipation of wildfires. We examine this possibility, below, with a specification that includes lead effects of wildfires, and find little

Table 3.3: Main specification predicting fuels reduction status of forested grid cells conditional on whether nearby WUI Census blocks experienced recent wildfires

	(1)	(2)	(3)	(4)	(5)
fireclose_t	0.0161	0.0182	0.0161	0.0167	0.0163
	(0.0038)**	(0.0039)**	(0.0037)**	(0.0042)**	(0.0041)**
	(0.0048)**	(0.005)**	(0.0043)**	(0.0053)**	(0.0051)**
fireclose_{t-1}	0.0074	0.0081	0.006	0.0058	0.0085
	(0.0032)*	(0.0024)**	(0.0025)*	(0.0027)*	(0.0033)*
	(0.0043)	(0.0031)**	(0.0028)*	(0.0031)	(0.0043)*
fireclose_{t-2}	0.0044	0.0058	0.0018	0.0051	0.0040
	(0.0032)	(0.0029)*	(0.0025)	(0.0033)	(0.0029)
	(0.0035)	(0.0032)	(0.0025)	(0.0035)	(0.0031)
fireclose_{t-3}	0.0001	0.0004	0.0011	0.0011	0.0005
	(0.0033)	(0.0029)	(0.0033)	(0.0035)	(0.0029)
	(0.0029)	(0.0024)	(0.0028)	(0.0025)	(0.0025)
fireclose_{t-4}	-0.0008	-0.0015	-0.0008	-0.0001	-0.0009
	(0.0025)	(0.0025)	(0.0027)	(0.0027)	(0.0025)
	(0.0025)	(0.0028)	(0.0025)	(0.0027)	(0.0023)
Fixed effects	Year	Year×unit	Year×district	Year×county	Year×tract
No. of groups	207,175	207,175	207,175	207,175	207,175
No. of obs.	1,864,575	1,864,575	1,864,575	1,864,575	1,864,575

Note: Regressions include grid cells within 5 km of any WUI Census block. Fireclose equals 1 if a fire occurred within 5 kilometers of a nearby Census block and 0 otherwise. The sample is limited to pixels NLCD classifies as forested in 2006. In addition to fixed effects noted in the table, all models include grid cell fixed effects. Robust standard errors are clustered by district first and unit second, ** p<0.01, * p<0.05.

relative to the average annual rate of fuels reduction projects in our sample. We also find a significant effect ($p < 0.05$) of a close fire that occurred one year previously, but only when we cluster the errors at the district level. This effect is smaller, indicating that a fire last year raises the probability of a fuels reduction project by 0.7 percentage points. Fires that occur two, three, and four years earlier do not have significant effects.

The inclusion of year-by-region effects sharpens the results. In models (2) through (5), the contemporaneous effect remains at approximately 1.6-1.8 percentage points, but

evidence for it.

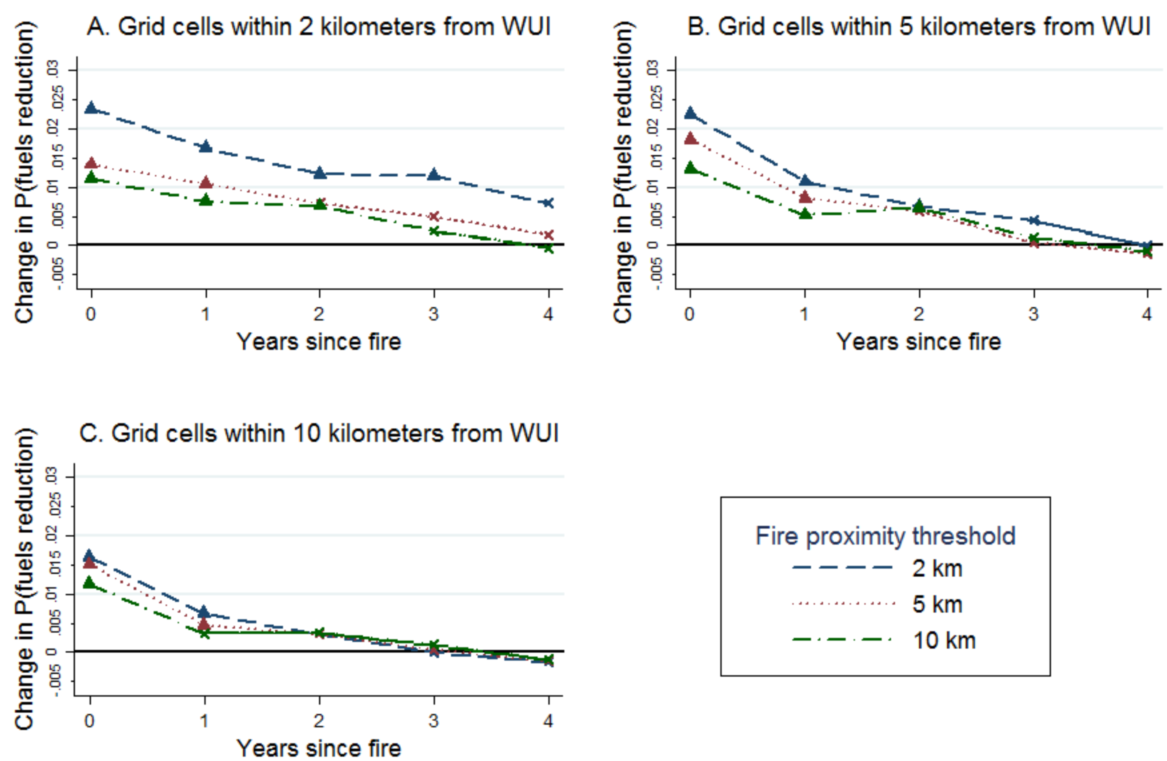
now the one-year lagged effect is significantly different from zero, whether clustering of standard errors is at the unit or district level. The results indicate that a close fire one year ago increases the probability of fuels management by 0.6 to 0.9 percentage points. In models (3), (4), and (5), longer lags do not have significant effects; however, the two-year lag in model (2) is significantly different from zero at the 5% level when standard errors are clustered at the district level. The estimate of 0.6 is lower than the one-year lagged effect (0.8), adding further evidence that the salience of wildfire risk diminishes with the time since the fire.

3.3.3 Sensitivity analysis and robustness checks

We conduct sensitivity analyses and robustness checks on our main specification. The first test evaluates the sensitivity of our results to the definition of close fires (fires within a distance c of the WUI) and close cells (cells within a distance d of the WUI). Figure 3.3 presents the coefficients on the $firedist$ variable for all combinations of $c = 2, 5, 10$ and $d = 2, 5, 10$, using version (2) of the model in Table 3.3. The lines in each panel correspond to different definitions of close fires and the three panels correspond to different definitions of close grid cells. For example, when we limit close fires and close cells to those within 2 km ($c = d = 2$; the dashed blue line in Panel A), we find that a close fire raises the probability of a fuels management project by approximately 2.5 percentage points. The effect is strong and persistent to a three-year lag (coefficient values marked by a solid triangle are significantly different from zero at the 5% level and those marked by an "x" are not).

Taken together, the results in Figure 3.3 provide support for the hypothesized salience mechanism and the use of distance to measure risk salience. First, fires that occur closer to WUI residents have larger effects. In all three panels, the dashed blue line, correspond-

Figure 3.3: Sensitivity analysis of thresholds for *fireclose* and *wuiclose*



Note: Coefficients marked with a solid triangle are significantly different from zero at a 5% significance level. Coefficients marked with an x are not significantly different from zero.

ing to fires within 2 km, is always above the dashed-dotted green line, corresponding to fires within 10 km. Expanding the fire proximity threshold (c) is likely to include fires that are not as salient to WUI residents. Second, for a given fire, salience effects are amplified at distances close to WUI residents. Lines in Panel A, corresponding to grid cells within 2 km of WUI blocks, tend to be higher than those in panel C, corresponding to grid cells within 10 km of WUI blocks. When we expand the size of the window around WUI blocks (d) we include fuels management projects that provide few benefits to WUI residents concerned with wildfire risk.

The second set of sensitivity analyses considers the possibility of serial correlation in our data. There may be negative serial correlation if management agencies are less likely to undertake a fuels management project in locations where fuels have recently been reduced. On the other hand, there may be positive serial correlation if projects take more than one year to complete or if fuels management projects take place in adjacent areas over several years and we mismeasure the precise boundaries of these activities.[19] Statistics in Table 3.2 show that, conditional on a fuels reduction project taking place, most grid cells receive fuels management only once. However, it is not uncommon for grid cells to receive fuels management two or more times. We address serial correlation by recoding the dependent variable so that a multi-year fuels management project appears as a single-year project (Table 3.4). For example, if $y_{it} = y_{it+1} = 1$, we recode the variables as $y_{it} = 1$, $y_{it+1} = 0$. In general, when we observe a cell with consecutive values of one, we set all but the first value to zero. This recoding procedure has the effect of purging the data of serial correlation due specifically to multi-year fuels reductions. We estimate all versions of the main specification with the recoded data and find little difference in the results.[20]

We estimate a version of equation (3.3) with one- and two-year leads (Table 3.5) as a placebo test, as we would not expect the likelihood of observing a fuels reduction project today to be influenced by the occurrence of future fires. Significant lead effects could be due to omitted time-varying cell-level factors that are correlated with wildfires and fuels reduction projects. Formally, lead parameters are included by modifying the summation term in equation (3.3) so that ℓ takes values from -4 to 2. A finding of insignificant lead coefficients gives us further confidence that we identify causal effects

[19]This is possible given the way we define boundaries for fuels reduction projects, described in section 3.2.

[20]Another way to test whether our results are robust to the possibility of serial correlation is with the estimator in Arellano and Bond (1991). We estimate versions of equation (3.3) that include one- and two-year lagged dependent variables. The results, available from the authors upon request, provide evidence of positive serial correlation. The coefficients on the lagged dependent variables are positive and significantly different from zero. Nevertheless, we still find evidence of contemporaneous effects of close fires on the likelihood of fuels management projects. The effects of fires in previous years are no longer significant, most likely because the lagged dependent variables absorb the effects of past fires.

Table 3.4: Test of robustness in which the dependent variable is recoded in order to examine the influence of multi-year fuels reduction projects

	(1)	(2)	(3)	(4)	(5)
fireclose_t	0.0155	0.0171	0.0162	0.0164	0.0159
	(0.0036)**	(0.0038)**	(0.0036)**	(0.004)**	(0.0039)**
	(0.0045)**	(0.0047)**	(0.0039)**	(0.0049)**	(0.0047)**
fireclose_{t-1}	0.0072	0.0071	0.0058	0.0056	0.0080
	(0.003)*	(0.0022)**	(0.002)**	(0.0024)*	(0.0032)*
	(0.0041)	(0.003)*	(0.0022)**	(0.0029)	(0.0043)
fireclose_{t-2}	0.0036	0.005	0.002	0.0047	0.0032
	(0.0026)	(0.0024)*	(0.0023)	(0.0028)	(0.0024)
	(0.0026)	(0.0027)	(0.0022)	(0.0027)	(0.0024)
fireclose_{t-3}	-0.0008	-0.0004	0.0011	0.0001	-0.0007
	(0.0027)	(0.0024)	(0.0028)	(0.0029)	(0.0025)
	(0.0024)	(0.0022)	(0.0023)	(0.0022)	(0.0023)
fireclose_{t-4}	-0.0012	-0.0017	-0.0004	-0.0007	-0.0019
	(0.002)	(0.0022)	(0.0024)	(0.0022)	(0.0023)
	(0.002)	(0.0022)	(0.0021)	(0.0022)	(0.002)
Fixed effects	Year	Year×unit	Year×district	Year×county	Year×tract
No. of groups	207,175	207,175	207,175	207,175	207,175
No. of obs.	1,864,575	1,864,575	1,864,575	1,864,575	1,864,575

Note: Regressions include grid cells within 5 km of any WUI Census block. Fireclose equals 1 if a fire occurred within 5 kilometers of a nearby Census block and 0 otherwise. The sample is limited to pixels NLCD classifies as forested in 2006. In addition to fixed effects noted in the table, all models include grid cell fixed effects. Robust standard errors are clustered by district first and unit second, ** p<0.01, * p<0.05.

of wildfires on government agency decisions and are not simply finding that agencies locate fuels management projects in areas that are likely to experience wildfires. The estimated coefficients on the lead variables are small relative to the contemporaneous and lagged parameters and not significantly different from zero with the exception of the two-year lead in models (2) and (5). Estimates of the other model coefficients are largely unaffected.

Although our data set only includes pre-fire fuels reduction projects (predominantly controlled burns and mechanical thinning), it is conceivable that some post-fire activities

Table 3.5: Placebo test in which two-year leads of *fireclose* are included in order to rule out joint determination of fire and fuel reduction project locations

	(1)	(2)	(3)	(4)	(5)
fireclose_t	0.0176	0.0204	0.0182	0.0188	0.0190
	(0.0045)**	(0.0048)**	(0.004)**	(0.0051)**	(0.0049)**
	(0.0059)**	(0.0063)**	(0.0049)**	(0.0065)**	(0.0062)**
fireclose_{t-1}	0.0105	0.0104	0.0084	0.0085	0.0117
	(0.0036)**	(0.0029)**	(0.003)**	(0.003)**	(0.0038)**
	(0.0049)*	(0.0035)**	(0.0032)**	(0.0035)*	(0.005)*
fireclose_{t-2}	0.0088	0.01	0.0041	0.0098	0.0081
	(0.0041)*	(0.0037)**	(0.0033)	(0.0042)*	(0.0039)*
	(0.0045)	(0.004)*	(0.0033)	(0.0044)*	(0.0043)
fireclose_{t-3}	0.0043	0.0037	0.0028	0.0051	0.0053
	(0.0041)	(0.0036)	(0.0039)	(0.0043)	(0.0038)
	(0.0033)	(0.0028)	(0.003)	(0.0029)	(0.0032)
fireclose_{t-4}	-0.0007	-0.0014	-0.0002	0.0004	-0.0002
	(0.003)	(0.003)	(0.0032)	(0.0032)	(0.0028)
	(0.0028)	(0.003)	(0.0029)	(0.0029)	(0.0028)
fireclose_{t+1}	0.0027	0.0042	0.0026	0.0026	0.0026
	(0.0027)	(0.0028)	(0.003)	(0.0028)	(0.0029)
	(0.0025)	(0.0028)	(0.0029)	(0.0027)	(0.0028)
fireclose_{t+2}	0.0039	0.0071	0.0058	0.0047	0.0062
	(0.0029)	(0.0031)*	(0.0036)	(0.0031)	(0.0031)*
	(0.0031)	(0.0036)*	(0.0041)	(0.0031)	(0.0035)
Fixed effects	Year	Year×unit	Year×district	Year×county	Year×tract
No. of groups	207,175	207,175	207,175	207,175	207,175
No. of obs.	1,450,225	1,450,225	1,450,225	1,450,225	1,450,225

Note: Regressions include grid cells within 5 km of any WUI Census block. Fireclose equals 1 if a fire occurred within 5 kilometers of a nearby Census block and 0 otherwise. The sample is limited to pixels NLCD classifies as forested in 2006. In addition to fixed effects noted in the table, all models include grid cell fixed effects. Robust standard errors are clustered by district first and unit second, ** p<0.01, * p<0.05.

could be misclassified as fuels management. Soon after a fire, land managers may thin trees, clear debris, and conduct salvage logging. In this case, we might interpret post-fire activities as a response by managers to heightened risk salience. We guard against this possibility by dropping all observations within the perimeter of an earlier fire (Table 3.6).

Table 3.6: Base specification with observations within the perimeter of previous fires removed to avoid misclassification of post-fire activities as fuels reductions

	(1)	(2)	(3)	(4)	(5)
fireclose_t	0.0121	0.0139	0.0115	0.0125	0.0125
	(0.0032)**	(0.0034)**	(0.0035)**	(0.0036)**	(0.0035)**
	(0.0039)**	(0.0042)**	(0.0039)**	(0.0044)**	(0.0041)**
fireclose_{t-1}	0.0031	0.0049	0.004	0.0031	0.0038
	(0.0028)	(0.0025)*	(0.0027)	(0.0028)	(0.0025)
	(0.0033)	(0.0028)	(0.0028)	(0.0029)	(0.0027)
fireclose_{t-2}	0.0033	0.0042	-0.0001	0.0037	0.0028
	(0.0035)	(0.003)	(0.0025)	(0.0036)	(0.0031)
	(0.0036)	(0.0032)	(0.0024)	(0.0036)	(0.0031)
fireclose_{t-3}	-0.0021	-0.0009	0.0000	-0.0006	-0.0018
	(0.0034)	(0.003)	(0.0033)	(0.0036)	(0.0029)
	(0.0029)	(0.0025)	(0.0028)	(0.0028)	(0.0025)
fireclose_{t-4}	-0.0006	-0.0011	-0.0008	0.0003	-0.0007
	(0.0026)	(0.0027)	(0.0028)	(0.0027)	(0.0029)
	(0.0026)	(0.0028)	(0.0027)	(0.0028)	(0.0024)
Fixed effects	Year	Year×unit	Year×district	Year×county	Year×tract
No. of groups	200,895	200,895	200,895	200,895	200,895
No. of obs.	1,770,739	1,770,739	1,770,739	1,770,739	1,770,739

Note: Regressions include grid cells within 5 km of any WUI Census block. Fireclose equals 1 if a fire occurred within 5 kilometers of a nearby Census block and 0 otherwise. The sample is limited to pixels NLCD classifies as forested in 2006, and pixels within the perimeter of previous fires have been removed. In addition to fixed effects noted in the table, all models include grid cell fixed effects. Robust standard errors are clustered by district first and unit second, ** $p<0.01$, * $p<0.05$.

This is likely an overly conservative approach as we may discard information about fuels reduction activities that occurred in response to a later fire occurring within the perimeter of an earlier fire. Nevertheless, we continue to find a significant contemporaneous effect and, in model (2), a one-year lagged effect that is significant at the 5% level.

3.3.4 Learning as an alternative to salience

An alternative interpretation of our empirical results is that government agencies learn about risks from future fires when a wildfire occurs. The key question to ask is, what information could a wildfire provide to land managers? In other words, what factors determine the likelihood of a future fire? Parisien et al. (2012) study the determinants of large wildfires in the western U.S. over the period 1984-2008. Their statistical analysis identifies three categories of variables — ignitions, climate, and topography/vegetation — that have statistically significant effects on the probability that a given grid cell burned in a large fire. Some of these factors are not applicable to our study of public forest lands (population density and land use) and others are controlled for by the grid-cell level fixed effects (topographic roughness, road density[21]) and year-by-region fixed effects in our model (large-scale measures of lightning strikes). Parisien et al. (2012) find that wildfire probability is predicted by a number of climate variables, including long-term temperature, precipitation, and wind speed means. It is conceivable that weather distributions changed over the period of analysis (i.e., climate change occurred) or that there were sustained periods of weather anomalies such as droughts or extended rainy periods. Wildfires may have alerted land managers to the effects of these events on future fire risk. However, because climate change and weather anomalies tend to be large-scale phenomena, they are also controlled for by the year-by-region fixed effects.[22] The smallest region used in our analysis is the Census tract, which has an average size of 364 km^2. For comparison, the area of the Isle of Wight in the United Kingdom is 380 km^2 and Lake Tahoe in the USA is 495 km^2 in size.

[21]Parisien et al. (2012) indicate that there was little year-to-year variation in topographic roughness and road densities over the period 1984-2008, which mostly covers our study period.

[22]Parisien et al. (2012) find that the capacity of a site to produce biomass, measured as gross primary productivity, is also associated with wildfires, but indicate that productivity is largely determined by climate.

Although we expect the fixed effects in our model to control for the key determinants of fire risk, we provide a formal analysis using the Vegetation Condition Class (VCC) measure described above. The VCC indicates the amount of fuels on the landscape and, thus, the potential for severe wildfires. If managers learn about vegetation conditions from local wildfires and the fixed effects in our model do not adequately control for fire risk, then the response to a nearby wildfire should be magnified when there are heavy fuel loads. We investigate this hypothesis by interacting the VCC variable with the treatment variable:

$$\begin{aligned} y_{it} = \alpha_i + & \sum_{\ell=-4}^{0} \beta^{\ell} \mathbb{1}\{\exists s \in S_i : firedist_{s,t+\ell} \leq c\} \\ & + \zeta \sum_{\ell=-4}^{0} [VCC_{i,t+\ell} \times \mathbb{1}\{\exists s \in S_i : firedist_{s,t+\ell} \leq c\}] + \delta_{tm(i)} + \epsilon_{it} \end{aligned} \tag{3.4}$$

where $VCC_{i,t+\ell}$ is the condition class for cell i in year $t+\ell$ and ζ is a model parameter. If the estimate of ζ is positive and significantly different from zero, then the effect of a wildfire on the probability of a fuels management project increases with fuels loads. However, results in Table 3.7 reveal an insignificant effect of VCC, in opposition to the learning model.[23] The original estimates of the β coefficients are unchanged when we include the VCC interaction term.

3.3.5 Additional support for the salience mechanism

To provide additional support for salience, we show that the effects of close fires vary with characteristics of WUI communities and the size of fires. We estimate two sets of

[23] In equation (3.4), ζ is restricted to be the same for the contemporaneous and lagged effects. We use this parsimonious specification because we do not have strong *a priori* reasons to expect the marginal effects of VCC to differ by the length of the lag. We estimated alternative models that allow each lag to have a different coefficient. Based on F-tests reported in Table 3.7 we cannot reject the null hypothesis that the coefficients are equal.

models with interactions similar to (3.4).[24] The first version is specified:

$$
\begin{aligned}
y_{it} = \alpha_i + &\sum_{\ell=-4}^{0} \beta^{\ell} \mathbb{1}\{\exists s \in S_i : firedist_{s,t+\ell} \le c\} \\
&+ \zeta \sum_{\ell=-4}^{0} \sum_{s \in S_i} [z_s \times \mathbb{1}\{firedist_{s,t+\ell} \le c\}] + \delta_{tm(i)} + \epsilon_{it}
\end{aligned}
\tag{3.5}
$$

where z_s is a characteristic of WUI block s or of the fire that treats block s. We define z_s as, alternatively, the population of the Census tract, the number of housing units in the Census tract, and logged fire size.[25] The second version of the model in (3.5) includes VCC as a control for objective fire risk.

Results in Table 3.7 reveal that the effects of a close wildfire are larger as the population and the number of housing units increase. The finding that salience effects vary with community characteristics confirms a prediction of our theoretical model and shows that local residents are part of the salience mechanism (see also Anderson et al. (2013)). The results are consistent with the preferences of residents being shaped by salient events or with government officials being affected by salience and operating on behalf of residents. The coefficient for fire size is positive but significantly different from zero at only the 8% level. The lack of significance may be due to the fact that the fire data we use only includes relatively large fires. Finally, we find that the effects of resident characteristics and fire size are unchanged when we control for landscape conditions with the VCC variable. This suggests that fuels management decisions depend on the risks perceived by WUI residents rather than on objective risks.

[24] As in equation (3.4), ζ is restricted to be the same for the contemporaneous and lagged effects. According to F-tests reported in Table 3.7, we cannot reject the null hypothesis that the coefficients are equal.

[25] We estimate the fire size version of the model with the sample used to produce Table 3.6. A large fire could augment salience but also limit the area available for fuels treatments. By using the restricted sample, our estimate measures only the first effect.

Table 3.7: Variation in salience effects by census block characteristics

	(1) Population	(2) Housing units	(3) Ln(Fire size)	(4) VCC
I. Interaction coefficient	1.1e-06	2.9e-06	.0011	-.0041
	(5.4e-07)*	(9.8e-07)**	(.00099)	(.0036)
II. Interaction coefficient	1.1e-06	2.9e-06	.0011	
	(5.4e-07)*	(9.8e-07)**	(.00099)	
VCC	.00068	.00065	.0012	
	(.00056)	(.00056)	(.00054)*	
Grid cells within past fire perimeters	Yes	Yes	No	Yes
No. demog. interaction lags	4	4	4	4
No. of groups	207,175	207,175	200,895	207,175
No. of obs.	1,864,575	1,864,575	1,770,739	1,864,575
F-statistic	0.3611	1.2714	0.2721	0.8673
Mean	4,949	2,359	8.96	2.38
Min	0	1	7.01	1.01
Max	36,146	9,905	12.4	3.86

Note: Row I presents the coefficient on the interaction terms as specified in Equations (3.4) and (3.5) and added to regressions as in column 3 of Table 3. Row II presents a set of separate regression results that also includes a control for vegetation condition class (VCC), whose coefficient is reported. Robust standard errors are clustered by unit, ** p<0.01, * p<0.05. Reported F-statistics use results from an unreported regression to test the null hypothesis that estimated ζ coefficients from regressions in row I are equal across lags of the interaction. An F-statistic less than 3.00 indicates insufficient evidence that ζ coefficients differ among lags. The reported mean, maximum, and minimum in each column correspond to sample statistics for each each column's variable (z_s) among all treated blocks.

3.4 Conclusions

The economics literature on salience has focused on how consumption of private goods is affected by salient features of the choice problem. In this paper, we extend this literature to examine how salience can affect the government provision of public goods. In our theoretical model, the benefits from a local public good are represented as a lottery. An exogenous shock makes a payoff more salient to residents of a community, causing them to over-weight the payoff in the salient state and miscalculate expected benefits. If the government bases its provision of the public good on expected benefits as expressed by the residents, then the allocation of the good will be inefficient. Samuelson (1954) recognized that the public may have incentives to misrepresent their preferences for a public good. In addition, there has been a long-running debate among economists about whether preferences for public goods can be reliably determined using direct elicitation methods (Diamond and Hausman, 1994; Hanemann, 1994; Carson, 2012; Hausman, 2012). In our case, the problem faced by the government is not deceit or flawed survey methods, but rather that the preferences expressed by the public have been biased by exogenous events.

The theoretical model in our paper provides insights into the nature of the inefficiency. We show that the allocation of the public good can increase even when the shock decreases one of the payoffs, which necessarily means that the true expected value of the good has declined. If the shock affects the higher-valued payoff, then enough weight can be shifted to this payoff such that the public's expected value for the good increases. This outcome is more likely to occur when the salience effect is large.

This result matches our empirical application, where we find support for the salience theory of public goods provision. We find that federal land management agencies in the western U.S. are more likely to locate fuels management projects near communities that have experienced a nearby wildfire. This increased response comes even as the recent wildfire has likely decreased the likelihood of loss from future fires. With our main specification, we estimate that the probability of a fuels management project increases by 1.6 to 1.8 percentage points in the year the fire occurs, declining to 0.6 to 0.9 percentage points in the year after the fire. These are relatively large changes considering that the average annual rate of fuels management projects on all forested lands in our sample is approximately 3.5% (see Table 3.2). Our finding that the effects of the nearby wildfire attenuate after one or two years does not necessarily mean that the salience of fire risk has diminished, as suggested by the results in McCoy and Walsh (2014). Our results are also consistent with a prompt response by the government that satisfies the increased demand for fuels management. One way to investigate the dynamics of salience would be to consider WUI blocks that experience nearby fires in multiple years and see how the effects change over time. For this analysis we would need a data set covering a longer time period.

The results of robustness checks support our claim that we identify salience effects. First, we find that the effects of nearby wildfires on the likelihood of observing fuels managment projects are strengthened when we focus our analysis on closer fires, which should be more salient to WUI residents (Figure 3.1). The effects also increase when we consider grid cells closer to WUI communities, suggesting that the federal agencies are responding to heightened demand for fuels management projects. Second, we find that effects of nearby wildfires increase with the population of the WUI community and the number of housing units (Table 3.7). These results suggest that the residents of WUI communities are part of the mechanism for determining the location of fuels management projects, consistent with our salience theory. Finally, we find evidence that contradicts alternative explanations for our results. The finding of insignificant coefficients on lead variables suggests that agencies are not simply locating fuels management projects in places that are likely to have fires. As well, our finding that vegetation condition does not magnify the effects of nearby fires guards against the possibility that our results reflect learning by agencies about the risk of future fires.

In addition to local public goods such as fuels management on public lands, salience could affect the government provision of national-level public goods. There are many examples of salient events that act as a catalyst for government action. In response to the Exxon Valdez oil spill in 1989, the U.S. Congress passed the Oil Pollution Act of 1990 that required double hulls on oil tankers. The Three Mile Island nuclear accident in 1979 led to stricter controls on nuclear plants and the outbreak of West Nile virus in New York City in 1999 prompted the creation of a national surveillance system for infectious diseases in the U.S. Catastrophic flooding of the Mississippi River has often been followed by government-funded levee building and other channel engineering projects (Wright, 2000). These may be rational responses by the government to new information about the demand for public goods. However, our paper offers an alternative explanation. The public's demand may be distorted by the salience of the catalyzing event, which would mean that the government response to heightened demand for public goods is inefficient.

Chapter 4

Inequality and government responsiveness: Evidence from salient wildfire events

Over the past several decades, there has been a movement toward government decision-making arrangements that encourage participation among stakeholders in the making and administration of policy. Proponents of participatory governance, as these arrangements are known, argue that greater participation will yield more effective and informed policy (eg. Pateman, 1970). In recent years, however, political scientists have recognized a potential tension between equitable outcomes and government responsiveness: if government is more responsive to some citizens than to others, inequitable policy outcomes may result. A substantial body of literature has examined how policymaker responsiveness (in terms of roll-call votes, or enacted policies) to constituent preferences varies across demographic groups (eg. Gilens 2005 or Bartels 2008). Yet policy outcomes only begin with legislation; downstream, disparities in responsiveness in the bureaucratic administration of policy can have implications for inequality as well.

In this paper, we study differential responsiveness among bureaucratic government agency administrators to demands from demographically-varying communities. Specifically, we focus on provision of wildfire risk reduction projects within the western U.S. In the western U.S., a large portion of the wildlands on which wildfires occur are federally-owned and managed. Therefore, federal land managers choices regarding fuel reduction project locations have potential to meaningfully influence wildfire risk. If projects are unduly awarded to favored communities, they have potential to exacerbate inequality.

Fuel projects may be disproportionately located near particular types of communities due to differences in agency responsiveness across communities. Alternatively, they may be disproportionately located near particular types of communities due to discrepancies in the degree of risk different types of communities face. For example, if individuals higher income individuals disproportionately choose to live in forested, high fire risk areas, we might also expect them to disproportionately benefit from fuels reduction projects. To distinguish between these two explanations, we use a quasi-experimental design motivated by our prior work on wildfire risk salience and demand for fuels projects. In chapter 3, we hypothesize that after wildfire events, when wildfire risk is at the top of homeowners minds, they will be more likely to demand agencies place fuels projects nearby. Our findings show that fuel project rates are 50-75% higher near communities that have recently experienced wildfire. Here, we use the occurrence of wildfire as an exogenous shock to demands for fuels projects. We then compare how responsiveness to these demands differs across demographically-varying communities. As in chapter 3, we find that federal fuels project rates increase near communities that have recently experienced wildfires; however, these increases are stronger for communities that are less diverse, more educated, and younger. In contrast to some of the existing literature, we do not find that income is a primary determinant of government responsiveness.

This paper makes two primary contributions to the literature. First, it contributes to the limited literature on bureaucratic decision-making and shows how differences in responsiveness among bureaucratic decision-makers can increase inequality. While over the last fifteen years a literature has emerged studying inequality in government responsiveness, this literature has for the most part ignored potential inequalities in policy administration. Our results suggest that this is a potentially important channel through which government policy can increase inequality. Second, this paper contributes to the literature on inequality in government responsiveness by using panel data and a quasi-experimental design to causally identify differences in responsiveness across communities. Findings within the existing literature are mixed, perhaps in part because existing studies either rely on cross-sectional or time-series data and therefore do not fully identify effects of responsiveness from other correlated factors.

Before proceeding to our study design and results, we will provide additional background regarding the extant literature, and the setting in which our study takes place. The next section discusses in greater detail the existing literature on government responsiveness and inequality, as well as the literature on bureaucratic decision-making and the role of interest groups. In section 4.1, we discuss wildfire management in the western U.S., the role of fuel reduction projects, and the planning process used by federal agencies in determining how and where to situate these projects. This process includes significant opportunities for public comment. We conclude section 4.1 by briefly describing existing work on the role of salience in responses to natural disasters. Our prior work on this topic describes how risk salience in the wake of a disaster can distort agency responses when public agencies are open and responsive to the demands of the public. This finding motivates the empirical strategy we develop in this paper, which we describe in section 4.3. In section 4.4, we discuss our results. We conclude by discussing implications of this research, as well as its limitations of this study and potential paths forward for future research.

4.1 Related Literature

As Wlezien and Soroka (2011) argue, increasing responsiveness may lead to increasingly inequitable outcomes under two conditions: (1) policy preferences must differ across groups, and (2) government responsiveness must vary across groups. Since the first condition is generally taken as given, research has focused on examining the second condition. Researchers have proposed a few possible explanations for possible differences in government responsiveness across demographic groups. First, a large literature indicates political participation varies across groups (eg. Verba et al., 1995), with higher income and higher SES individuals participating at higher rates. These groups may apply greater pressure to politicians and government officials. Another reason to expect that government officials might respond differentially to high SES groups is that politicians and government officials tend to be high SES themselves. Government officials tend to be relatively high income, highly educated individuals, and they may be more sympathetic to the views of similar individuals (Page et al., 2013).

Motivated by these ideas, a variety of studies over the past fifteen years have tested for inequality in responsiveness among policy-makers, usually by following Gilens (2005) in relating political outcomes (eg. roll-call votes, legislation) to constituent opinions across the income distribution. So far, however, these studies have not yielded a consensus regarding bias among policymakers. As Kelly and Enns (2010) point out, studies that find that policymakers are more responsive to higher income individuals tend to rely on cross-sectional policy outcome data (eg. Gilens, 2005; McCarty et al., 2009; Gilens, 2011). On the other hand, studies that make use of time-series data (eg. Ura and Ellis, 2008; Wlezien and Soroka, 2011) cannot identify differences in responsiveness across income groups because shifts in political opinions over time tend to be correlated across income groups.

More recently, researchers have begun to examine differences in responsiveness outside of the policy-making process. The two studies most closely related to this paper are Sances (2016) and Grimes and Esaiasson (2014), both of which examine inequality in responsiveness among local government officials. Grimes and Esaiasson 2014 study siting of locally undesirable land uses, such as waste facilities, in Sweden. Consistent with the environmental justice literature (Ringquist, 2005), they find that locally undesirable land uses are more likely to be placed near low SES communities. However, they find that electoral participation more strongly predicts siting decisions than income. A weakness of this study is that it relies on cross-sectional data. It is likely that individuals with low propensity to participate in the political process might sort into inexpensive, undesirable locations, which might also be more likely to become sites of waste facilities. Sances (2016) use panel data, as well as an exogenous shift in responsiveness caused by a change in how local assessors are chosen, to study effects of decreased responsiveness across the income distribution. He finds that towns that with elected assessors are less likely perform property value reassessments, which tend to increase the effective tax rate paid by owners of high-value homes. Throughout the literature on government responsiveness and inequality, data limitations have led to difficulty in identifying differences in responsiveness across groups. Like Sances (2016), we add to this literature by making use of panel data to credibly identify these differences.

Further, we explore an as yet unexplored avenue through which government programs yield unequal outcomes. Most studies examining inequality in government responsiveness have focused on responsiveness among elected officials. This makes sense, given that elected officials tend to be more responsive to demands from the public than appointed officials or bureaucrats (Besley and Coate, 2003; Canes-Wrone et al., 2014; Whalley, 2013). Nevertheless, while bureaucratic decision-making is motivated by a diverse set of factors, including budget maximizing (Niskanen, 1971), concerns regarding career advancement (Dewatripont et al., 1999), and intrinsic motivations (Besley and Ghatak, 2005; Prendergast, 2007), satisfying demands of the public may be an important motivation. A large literature points to the influence interest groups can have on bureaucratic decision-making. As the next section will discuss, interest groups may be particularly influential in the case of environmental management within the U.S., which since the 1970s has required government administrators to engage the public within the planning process.

4.2 Wildfire fuels projects and federal land management

Over the past several decades, wildfire activity has sharply increased within the western U.S. (Dennison et al., 2014). Since the 1970s, the annual number of large wildfires (fires larger than 400 hectares) within the western U.S. has increased by over 500 percent, while area burned in large wildfires has increased by over 1200 percent (Westerling, 2016). Researchers have generally attributed this trend to the combined effects of climate change (eg. Westerling et al., 2006; Abatzoglou and Williams, 2016) and high fuel loads within western forests (Arno et al., 1995; Keane et al., 2002; Naficy et al., 2010). For much of the twentieth century, the US Forest Service (USFS) and other public agencies took an aggressive stance toward suppressing wildfires. The effects of fire exclusion differ across forest types; however, in many open canopy western forests where frequent low intensity fires have historically removed understory brush and debris, fire exclusion has led to a build-up of ladder fuels, which carry fire from a forests understory to its canopy. In these forest types (eg. dry forests such as ponderosa pine forests within the U.S. southwest and Sierra Nevada mountains), fire exclusion has increasingly led to larger and more severe wildfires (Schoennagel et al., 2004). As wildfire activity has increased, so too has federal spending on wildfire management. The US Forest Service now consistently spends approximately 50 percent of its annual discretionary budget on wildfire management, while in 2000 it spent less than 20 percent (Thompson et al., 2015). The agency, which incurs approximately 70 percent of total federal suppression costs, spent nearly $2.4 billion on fire suppression in 2017. Of this, $375 million were spent on hazardous fuel removal projects (USFS, 2017).

Wildfire fuels projects are projects intended to reduce wildfire risk by restoring the forest to conditions under which high intensity fires are less likely. Fires that burn in the forest canopy (called crown fires) are hotter and more difficult to contain; therefore, fuel projects are generally designed to remove fuels that promote crown fires. In particular, fuel projects aim to remove surface and ladder fuels, which can cause a fire to burn into the forest canopy, and to reduce the density of the forest canopy, which reduces potential for crown fire spread (Agee and Skinner, 2005). These goals are generally achieved either by prescribed fire, or by mechanical thinning. In a prescribed fire, the forest understory is burnt under favorable conditions to remove surface and ladder fuels. Under mechanical thinning, heavy equipment is used to remove trees from the stand to reduce canopy density. Empirical evidence (reviewed in Kalies and Kent, 2016) indicates that fuel reduction projects within dry forests in the western U.S. are effective in reducing fire intensity, especially when prescribed fire and thinning are used in conjunction.

There is also some evidence that strategically-placed fuels projects can help prevent damage to homes and structures. During the 2011 Wallow Fire in Arizona, fuels projects placed adjacent to a residential area resulted in reduced fire severity (Kennedy and Johnson, 2014), and have been credited with saving homes by providing firefighters with opportunities to them (Bostwick et al., 2011). Unfortunately, while federal spending on fuels projects has increased over the past several decades, federal agencies are budget constrained, and they cannot implement fuels projects everywhere they are needed. Therefore, federal agencies may face competition among residential areas for their limited resources.

While scientific management is a foundational doctrine of the USFS, previous research indicates that USFS and other federal land management agencies decision-making is frequently influenced by public pressure (Sabatier et al., 1995; Johnson and Watts, 1989). This may in part be due to the participatory decision-making structures that have defined federal land management planning since the passage of the National Environmental Policy Act (NEPA) in 1970. NEPA mandates that all federal agencies must document actions that will significantly impact the environment with an Environmental Impact Statement (EIS). Further, it mandates a public comment period during which the public can comment on the proposed action. Similarly, the National Forest Management Act of 1976 mandates that the public be allowed opportunities to comment on forest management plans. This openness to public input likely affects the fuel project planning process. According to Hakanson (2010), forest managers often have an eye toward the NEPA process from a fuel projects conception.

In chapter 3, we investigate how, when agencies are responding to public pressure, behavioral biases such as salience can lead them to make inefficient decisions. Salience is a behavioral phenomenon in which individuals' disproportionately weight concerns that have drawn their attention (Taylor and Thompson, 1982). Salience frequently distorts human responses to natural disasters, and can lead to inefficient or potentially even maladaptive responses to these events (Anderson et al., 2018). Prices of homes in areas of high fire or flood risk are lower than homes outside these areas, but only in years after a fire or flood has occurred nearby (McCoy and Walsh, 2014; Bin and Landry, 2013). Corporate managers increase cash holdings after hurricane events, despite the fact that the hurricane event did not alter the base level of risk (Dessaint and Matray, 2017). In the political science literature, salient disaster events are referred to as focusing events, and have been shown to influence political agenda-setting (Birkland, 1997). In chapter 3, we found that federal wildfire fuels management projects are more likely to be placed near communities that have experienced recent wildfires. We attribute this pattern to salience of wildfire risk in these areas, and the ensuing public pressure community members place on agencies. Here, we use the occurrence of wildfires as a shock to public pressure, and use this to identify differential rates of bureaucratic responsiveness across demographic groups.

4.3 Methods

Our units of observation in this paper are U.S. Census blocks from 15 western U.S. states.[1] We focus specifically on blocks on classified as wildland urban interface (WUI) in 2000, since these are communities that are likely to face wildfire risk. Because we are interested in determinants of public fuel management project locations, we further limit our sample of Census blocks to those within 10 km of public lands managed by the US Forest Service (USFS), Bureau of Land Management (BLM), or National Park Service (NPS). The USFS, BLM, and NPS together manage approximately 1.5 million square kilometers of land in the western U.S., and are responsible for 93% of federal fuels management projects within the timespan of our data. After these restrictions, our data comprises more than 320 thousand census blocks.

Data regarding fuel treatment locations come from the National Fire Plan Operations and Reporting System (NFPORS). Our NFPORS data set records the point location (latitude and longitude), dates, and area of all fuels reduction projects conducted by the

[1] The states comprise US Forest Service regions 1-6. They are Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, North Dakota, South Dakota, Utah, Washington, and Wyoming.

Table 4.1: Summary statistics for dependent variables

	Dep. vars. measuring fuel projects near WUI block		
Radius	Indicator	Percent public land	Total area (sq. km)
2 kilometers	.027	.0064	.065
5 kilometers	.074	.0093	.3
10 kilometers	.16	.011	1.1
Number of WUI blocks	322,683	322,683	322,683
Number of block-year obs.	5,035,247	5,485,611	1,942,522

USFS, BLM, and NPS during years 2003-2011. Since NFPORS does not provide fuels project boundaries, we used reported point locations and project areas to impute project boundaries, under the assumption that project boundaries are circular. We compare variation across WUI blocks in the degree to which fuels project are placed nearby, and we measure fuels projects three ways. First, we use as a dependent variable an indicator for whether any fuels projects were placed within a given distance of a WUI block in a given year. As two additional dependent variables, we measure the percentage and total area of public lands that were treated within some distance of a WUI block in each year. Average values of each of the three dependent variables are provided in Table 4.1, where the table's rows vary in the radius around each WUI block within which fuels projects are measured.

Data on the occurrence of fires are drawn from the USGS Monitoring Trends in Burn Severity (MTBS) project, which uses satellite remote sensing data to map all large fires occurring within the U.S. Within the western U.S., MTBS maps all fires larger than 1,000 acres. Therefore, while the MTBS data do not include all fires within the period, they include the largest and therefore likely the most salient wildfires. We measure the distance from each census block to the nearest wildfire in each year over the years

Table 4.2: Rate at which WUI blocks received nearby fuel treatments, for full sample and for WUI block-years in which a recent nearby fire has occurred

	Full sample	Block-years with recent fire within distance		
		2 kilometers	5 kilometers	10 kilometers
Distance from WUI block				
2 km	0.03	0.09	0.07	0.05
	108,734	8,856	17,227	29,397
5 km	0.07	0.16	0.13	0.12
	335,994	21,263	46,279	86,706
10 km	0.16	0.29	0.24	0.22
	781,638	47,369	103,243	200,343
Number of WUI blocks	322,683	39,303	85,128	144,934
Number of block-year obs.	5,035,247	160,911	427,669	914,102

2000-2011, and we define the indicator $recentfire_{it}$ as equal to one for blocks that have experienced a wildfire within some threshold distance in the past 3 years. Columns 2-4 of Table 4.2 report fuels project rates after the sample has been limited to those blocks for which a fire has occurred within 2, 5, and 10 kilometers, respectively. Comparing fuel projects rates in these columns with column 1 of Table 4.2, which reports the percent of sample overall receiving treatments within a given radius, blocks are more likely to receive a fuels project when they have experienced a recent nearby fire.

We hypothesize that the observed increase in fuels project rates may be due to heightened salience of wildfire risk in these areas. Where wildfire risk is more salient, homeowners and community members may apply greater pressure on public land management agencies to reduce wildfire hazard. However, while the pattern of fuels project rates observed in Table 4.2 is consistent with this hypothesis, there are other explanations as well. Areas with higher wildfire risk are more likely to have experienced recent wildfires, and are more likely to be chosen as the location for fuels reduction projects. To separate the effect of a recent wildfire from the fixed wildfire risk within an area, we make use

Table 4.3: Demographic and political characteristics for the entire sample of WUI blocks, and for WUI blocks receiving nearby fuel reduction projects

			Block-years with fuels projects within distance		
	Full sample		2 kilometers	5 kilometers	10 kilometers
Population density	1541.1	[4400.5]	684.2	1070.6	1282.4
Per cap. income	21365.9	[10205.8]	22241.0	21818.6	21479.3
Percent older than 65	13.3	[6.65]	13.6	13.7	13.5
Percent high school grad.	84.0	[10.0]	86.9	86.5	85.7
Percent college grad.	23.8	[14.7]	25.3	25.7	25.2
Percent white	83.9	[16.2]	90.6	89.5	88.0
Percent American Indian and Alaska Native	3.20	[11.0]	1.99	1.96	2.10
Percent Hispanic or Latino	14.0	[16.9]	8.62	9.35	10.8
Number of WUI blocks	322,683		9,042	19,169	25,933
Number of block-year obs.	3,872,196		108,734	335,994	781,638

Note: Standard deviations are included within brackets.

of the panel structure of our block-level data set and include in our estimating equation a full set of WUI block fixed effects. These effects account for fixed differences across blocks in the rate at which projects are implemented on surrounding land.

Finally, we collected a series of variables describing each block's demographic characteristics. Demographic variables include a series of income, education, age, and race and ethnicity variables measured at the Census tract level, as well as population density, which is measured at the Census block level (US Census Bureau, 2000). Since our fuels treatment data span the years 2003-2011, we use demographic variables from the 2000 Census, and therefore our demographic variables are not measured as time-varying. Column 1 of Table 4.3 reports the means and standard deviations of demographic variables within our sample of WUI blocks. To ease interpretation of regression results, each demographic variable is standardized so that it is distributed with mean zero and a standard deviation of 1.

Columns 2-4 of Table 4.3 report means of demographic variables within block-years receiving fuel reduction projects within 2, 5, and 10 kilometers, respectively. Since demographic variables are not observed as time-varying, means for demographic variables are means of demographic variables that ever received fuels projects within for example, 2 kilometers, weighted by how frequently they received fuels projects. Blocks for which fuels projects occur more frequently nearby tend to be less dense, wealthier, and more educated. Most significantly, when fuels projects occur within 2 km of WUI blocks, these blocks are 90 percent white, while blocks within the sample overall are 83.6 percent white.

Patterns in demographic variables are largely consistent with our hypotheses. Wealthier, whiter, and more educated Census blocks are more likely to receive fuels projects. However, these patterns in and of themselves should not be interpreted as evidence that managers are more responsive to such individuals. For example, these patterns could also emerge due to amenity-driven sorting. Whiter, wealthier, and more educated individuals may be more likely to live in high amenity, high fire risk areas, and these areas are likely to be chosen as the location for fuels reduction projects. To identify differences in responsiveness to demographics, we make use of the occurrence of fires, which after accounting for fixed differences across salience of wildfire risk within an area provide a plausibly exogenous shock to public demand for fuels projects.

Formally, we model dependent variables y_{it}, which each measure the placement of fuel projects in the area surrounding block i in year t, using a standard difference-in-differences framework. We take WUI blocks as treated if they have experienced a nearby wildfire in the past three years. We choose three years as the relevant cut-off because our work in chapter 3 indicates that salience of wildfire events is short-lived, and does not drive fuel project decision-making after about 3 years.[2] We define nearby fires as those occurring within 2 km of a WUI block, since we believe very nearby fires will be most salient to homeowners and most likely to drive increases in public pressure. Therefore, we

[2]This finding is also consistent with other empirical work on the effects of salient disaster events on home prices, eg. McCoy and Walsh (2014).

define the variable $recentfire_{it}$ as equal to 1 if WUI block i experiences a wildfire within 2 km in the past three years and zero otherwise. We write the difference-in-difference specification as:

$$y_{it} = \alpha_i + \beta recentfire_{it} + recentfire_{it} \times \mathbf{x}_i' \boldsymbol{\gamma} + \delta_{rt} + \varepsilon_{it}. \tag{4.1}$$

The coefficient β describes the main effect of a recent fire on the placement of fuels projects. Because we are interested in how responsiveness to salient wildfire events varies with demographics across communities, we allow the effect to vary with demographic characteristics. The degree to which the effect of wildfire occurrence varies with demographic variables is captured by the $K \times 1$ vector of parameters $\boldsymbol{\gamma}$. Given that demographic variables are standardized to a distribution with mean zero and a standard deviation of 1, every element γ_k of $\boldsymbol{\gamma}$ can be interpreted as describing increases in responsiveness due to a 1 standard deviation increase in demographic variable k. In order for β and $\boldsymbol{\gamma}$ to be identified, it is required that there exist no unobserved factors within the error term ε_{it} that are correlated with the occurrence of a recent fire, and lead to an increase in area receiving fuels projects near WUI block i. Due to amenity-driven sorting, higher socioeconomic status individuals may be more likely to live in areas with higher wildfire risk and higher fuels project rates (Stetler et al., 2010). To account for fixed differences in the fuels project rates across blocks, we include block-level fixed effects α_i.

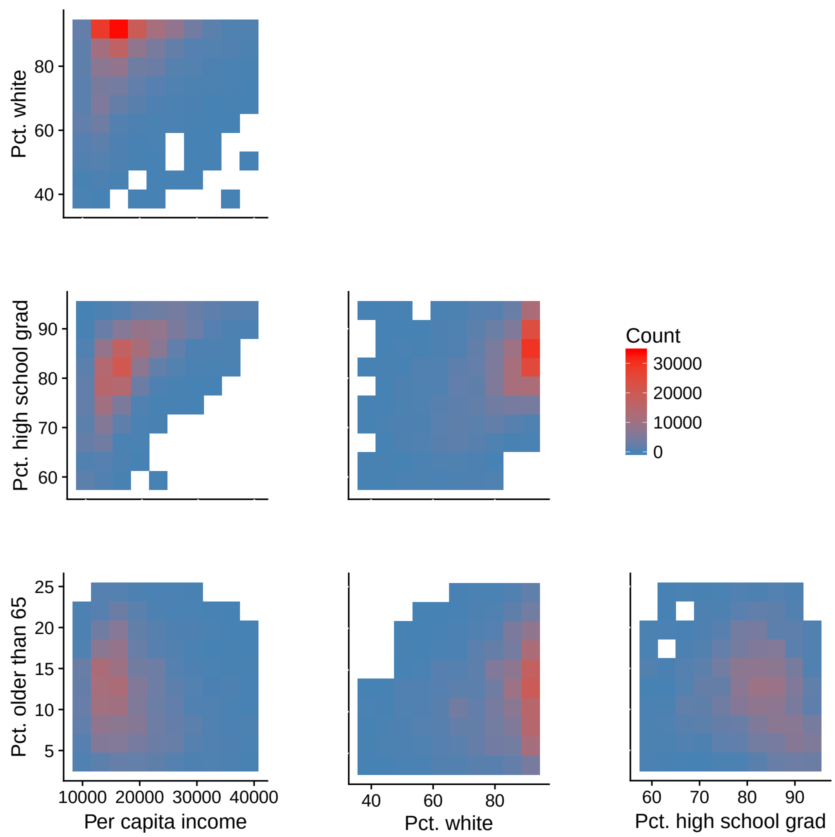
Still, a threat to identification would exist if wildfire risk facing individual wildland urban interface blocks were to vary over time in a way that were correlated with block demographic characteristics. To guard against this possibility, we include a set of county-by-year fixed effects—denoted δ_{rt}, where r indexes counties—which account for differences across counties and within years, in fuels project rates. After including block and county-by-year fixed effects, we identify β and $\boldsymbol{\gamma}$ using variation in differences between departures from the the within county-by-year average fuel project rate for cell i in year t, and the average departure from the within county-by-year fuel project rate across all years for cell i.

Fuels project rates are spatially correlated, both due to underlying spatial correlation in wildfire risk and mechanically due to the way in which our dependent variables are constructed. Our dependent variables are defined as a function of the placement of fuel projects within some distance from a given block. However, the same fuels project may increase the project rates for multiple adjacent WUI blocks. Moreover, treatment is not randomly assigned to blocks. It is spatially correlated, since a fire that occurs near one block also occurs within the proximity of adjacent blocks. To account for non-independence among observations within our sample of blocks, we cluster standard errors by Census tract. Census tracts are generally quite large within the western U.S. Our sample of nearly 5.5 million blocks, but contains only 5,470 tracts across 473 counties.

4.4 Results

We are interested in how bureaucratic responsiveness varies across different types of communities. In particular, we are interested in how responsiveness varies with per capita income, educational attainment, racial composition, and age. Unfortunately, within our sample of WUI communities these variables are highly correlated. Figure 4.1 illustrates joint distributions for demographic variables within the sample of WUI blocks. The upper left panel, for example, indicates that blocks are most likely to have a very high percentage of white residents and per capita income of approximately $20,000. Further, it shows that very few blocks are observed to have a low percentage of white residents, but a high per capita income. Similarly we do not observe blocks with high per capita income but low levels of educational attainment, or blocks with a high percentage of

Figure 4.1: Joint distribution of demographic variables within the sample of WUI blocks. Observations above or below or the 97.5 or 2.5 percentiles, respectively, for any demographic variable have been dropped from the sample.



senior citizens but a low percentage of white residents.

The strong correlations among demographic variables within our sample makes it difficult to separately identify which variables bear primary responsibility for any differences in responsiveness. Therefore, in Tables 4.4-4.6, we test the effect of demographic characteristics on responses to wildfire events in two ways. First, in columns 1-5 of each table, we test how responses vary with individual demographic characteristics. A disadvantage of these results is that because demographic characteristics are highly correlated, it is not possible to know for example whether differences in responses are due to differences in education or differences in racial composition. In column 6, we include each of the demographic interactions together in the same regression. This model provides insights into which of these demographic variables is most responsible for driving differences in responsiveness across locations. However, because demographic variables are highly correlated with one another, interaction coefficients within this model are not estimated with great precision.

Table 4.4 provides estimates of equation 4.1, where the dependent variable is an indicator for whether any public lands within 2 km of WUI block i received fuel treatments in year t. Therefore, the model can be interpreted as a linear probability model. The coefficient reported in column 1 indicates that the probability a fuels project is placed within 2 km is more than 2 percentage points higher for blocks that have experienced a wildfire within 2 km in the past three years. Table 4.1 indicates that approximately 3 percent of blocks receive projects within 2 kilometers in a given year; therefore, recent fires cause an approximately 75% increase in the probability a fuels project will be placed nearby. This result is similar to the result reported in chapter 3. Columns 2 and 3 indicate that the magnitude of this effect doubles when the percentage of white residents or the percentage of high school graduates within a block increases by 1 standard deviation (16 percentage points or 10 percentage points, respectively). The probablity of receiving a project is approximately 1.2 percentage points higher for blocks with per capita income that is 1 standard deviation above the mean; however, this difference is not statistically significant at the 5 percent level. Finally, blocks with a one standard deviation higher percentage of senior citizens are 1.2 percentage points less likely than average to receive nearby fuels projects after the occurrence of a fire. When these variables are included together in the same regression, standard errors increase due to high correlation among demographic variables. Nonetheless, the regression estimates indicate that whiter and younger blocks are more likely to receive fuels projects in the wake of a wildfire event. Interestingly, variation in per capita income does not appear to be a primary driver of re-

Table 4.4: Linear probability model of the probability a fuels project is undertaken within 2 km of a WUI block, as a function of indicator for whether fire has occurred within 2 km of the WUI block in the past 3 years and community characteristics interacted with the indicator. The sample is limited to WUI blocks with at least one public lands grid cell within 2 km.

	(1)	(2)	(3)	(4)	(5)	(6)
Fire within 2 km	.022*	.021*	.02*	.021*	.02*	.018*
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Interactions with nearby fire						
Pct. white		.02**				.017**
		[0.01]				[0.01]
Pct. high school grad.			.023*			.011
			[0.01]			[0.01]
Per cap. income				.012		.0015
				[0.01]		[0.01]
Pct. older than 65					-.012*	-.014**
					[0.01]	[0.01]
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number obs.	4043671	4043671	4043535	4043671	4043671	4043535
Number of WUI blocks	237,863	237,863	237,855	237,863	237,863	237,855
Number of county-years	7,837	7,837	7,837	7,837	7,837	7,837

Note: Robust standard errors are clustered by Census tract, ** $p < 0.01$, * $p < 0.05$.

sponsiveness. This finding differs from much of the literature on inequality in government responsiveness (Gilens, 2005; McCarty et al., 2009; Gilens, 2011).

Table 4.4 captures differences in the extent to which blocks are treated, but may underestimate differences in responsiveness if managers are not only more likely to implement projects but are also more likely to implement larger projects around certain types of blocks. In Table 4.5 we use as the dependent variable the percentage public lands within 2 kilometers on which fuels projects are implemented, and we report results from the same set of regressions as in Table 4.4. Occurrence of fire near a WUI block increases the percentage area receiving projects by about 0.8 percent, where on average 0.6% of public lands within 2 km of a WUI block receive fuels projects in a given year

(Table 4.1). This effect varies with demographic variables similarly to the effect observed in the previous table. One concern is that there may be greater capacity for responsiveness to blocks that are near large areas of public lands, and that these blocks may be more likely to have low diversity and high per capita income. To examine whether dividing area with fuels projects by total area of public lands biases our results, in Table 4.6 we again perform the same set of regressions, but use area receiving fuels projects within 2 kilometers as the dependent variable. Results are consistent with the previous regressions. The average block receives 0.065 square kilometers of fuel projects within 2 kilometers in a given year. When a fire has occured near a WUI block in the previous three years, the block receives 0.26 square kilometers in additional fuel projects. This effect tends to increase as the block becomes less diverse and younger.

4.5 Discussion

In this paper, we find that forest managers are more likely to implement fuels projects near communities that have recently experienced a fire, especially if those communities have a higher percentage of white or young residents. The literature on government responsiveness and inequality tends to focus on variation in responsiveness across levels of per capita income. In general, it does not explore whether other demographic characteristics, which may be correlated with per capita income, instead drive differences in responsiveness. Our results suggest that demographic characteristics such as race and age may be important in explaining differences in responsiveness. In contrast to much of the literature on inequality in government responsiveness, we find no relationship between responsiveness and community per capita income, even when per capita income is included in regressions as the sole demographic interaction. It is possible that we fail to observe an effect of income on responsiveness because government bureaucrats face a

Table 4.5: Regression of the percent of public lands within 2 km of a WUI block receiving a fuel project on an indicator for whether fire has occurred within 2 km of the WUI block in the past 3 years and community characteristics interacted with the indicator. The sample is limited to WUI blocks with at least one public lands grid cell within 2 km.

	(1)	(2)	(3)	(4)	(5)	(6)
Fire within 2 km	.0078*	.0075*	.007*	.0075*	.0073*	.0065*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Interactions with nearby fire						
Pct. white		.0081**				.0068**
		[0.00]				[0.00]
Pct. high school grad.			.0088*			.0042
			[0.00]			[0.00]
Per cap. income				.0049		.00089
				[0.00]		[0.00]
Pct. older than 65					-.0039*	-.0044*
					[0.00]	[0.00]
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number obs.	4043671	4043671	4043535	4043671	4043671	4043535
Number of WUI blocks	237,863	237,863	237,855	237,863	237,863	237,855
Number of county-years	7,837	7,837	7,837	7,837	7,837	7,837

Note: Robust standard errors are clustered by Census tract, ** $p < 0.01$, * $p < 0.05$.

different set of incentives than do elected officials. While elected officials may be concerned about pleasing voters more likely to donate to campaigns, bureaucrats may be implicitly biased toward citizens with whom they are more similar. On the other hand, it is possible that we observe no relationship between income and responsiveness simply due to insufficient variation across blocks in per capita income. This explanation seems especially likely since we find evidence that responsiveness is correlated with education levels, and education is correlated with income.

An important limitation to this paper is that because we have no direct measure of citizen political engagement, we cannot discern whether differences across communities in fuel project rates after fires are due to differences in salience-motivated political action,

Table 4.6: Regression of fuel project area within 2 km of a WUI block on an indicator for whether fire has occurred within 2 km of the WUI block in the past 3 years and community characteristics interacted with the indicator. The sample is limited to WUI blocks with at least one public lands grid cell within 2 km.

	(1)	(2)	(3)	(4)	(5)	(6)
Fire within 2 km	.26*	.3*	.23*	.24*	.27*	.33**
	[0.11]	[0.12]	[0.10]	[0.10]	[0.11]	[0.12]
Interactions with nearby fire						
Pct. white		.31*				.38**
		[0.13]				[0.14]
Pct. high school grad.			.21			.058
			[0.11]			[0.10]
Per cap. income				.061		-.061
				[0.06]		[0.05]
Pct. older than 65					-.13*	-.2**
					[0.05]	[0.08]
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number obs.	500,633	500,633	500,633	500,633	500,633	500,633
Number of WUI blocks	29,449	29,449	29,449	29,449	29,449	29,449
Number of county-years	850	850	850	850	850	850

Note: Robust standard errors are clustered by Census tract, ** $p < 0.01$, * $p < 0.05$.

or to responsiveness *per se*. If the occurrence of a wildfire induces a uniform shock to demands communities place on land management agencies, we would be able to interpret differences in post-fire effects on project rates strictly to government responsiveness. It is possible that, however, that in the wake of a wildfire event, certain communities are more likely to become politically engaged and to comment on proposed fuels management projects. If so, differences we observe in post-fire effects on project rates may be due to differences across communities in shocks to demand induced by wildfires. Whether our results are due to differences in responsiveness *per se* or differences in shocks to demand, this paper shows that similar events can yield very different policy outcomes for different types of communities. Further, it indicates inequality in government responsiveness extends beyond policymaking to the implementation of policy by government bureaucrats.

Bibliography

Abatzoglou, J.T. and Williams, A.P. 2016. "Impact of anthropogenic climate change on wildfire across western US forests." *Proceedings of the National Academy of Sciences* 113(42):11770–11775.

Abrevaya, J. and Hamermesh, D.S. 2012. "Charity and favoritism in the field: Are female economists nicer (to each other)?" *Review of Economics and Statistics* 94(1):202–207.

Agee, J.K. and Skinner, C.N. 2005. "Basic principles of forest fuel reduction treatments." *Forest ecology and management* 211(1-2):83–96.

Allen, C., Savage, M., Falk, D., Suckling, K., Swetnam, T., Schulke, T., Stacey, P., Morgan, P., Hoffman, M., and Klingel, J. 2002. "Ecological restoration of southwestern Ponderosa pine ecosystems: A broad perspective." *Ecological Applications* 2002(5):1418–1433.

Anderson, S.E., Bart, R.R., Kennedy, M.C., MacDonald, A.J., Moritz, M.A., Plantinga, A.J., Tague, C.L., and Wibbenmeyer, M. 2018. "The dangers of hazard-driven responses to climate change." *Nature Climate Change,* Published online June 11, `https://doi.org/10.1038/s41558-018-0208-8`.

Anderson, S.E., Hodges, H.E., and Anderson, T.L. 2013. "Technical management in an age of openness: The political, public, and environmental forest ranger." *Journal of Policy Analysis and Management* 32(3):554–573.

Arellano, M. and Bond, S. 1991. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *The Review of Economic Studies* 58(2):277–297.

Arno, S., Scott, J., and Hartwell, G. 1995. "Age-class structure of old growth Ponderosa pine/Douglas-fir stands and its relationship to fire history, INT-RP-481." USDA Forest Service, Intermountain Research Station. Ogden, Utah, USA.

Barseghyan, L. and Coate, S. 2014. "Bureaucrats, voters, and public investment." *Journal of Public Economics* 119:35–48.

Bartels, L.M. 2008. *Unequal democracy: The political economy of the new gilded age.* Princeton University Press, Princeton, New Jersey.

Besley, T. and Coate, S. 2003. "Elected versus appointed regulators: Theory and evidence." *Journal of the European Economic Association* 1(5):1176–1206.

Besley, T. and Ghatak, M. 2005. "Competition and incentives with motivated agents." *American Economic Review* 95(3):616–636.

Bin, O. and Landry, C.E. 2013. "Changes in implicit flood risk premiums: Empirical evidence from the housing market." *Journal of Environmental Economics and Management* 65(3):361–376.

Birkland, T.A. 1997. *After Disaster: Agenda Setting, Public Policy, and Focusing Events.* Georgetown University Press, Washington, DC.

Bordalo, P., Gennaioli, N., and Shleifer, A. 2012a. "Salience in experimental tests of the endowment effect." *The American Economic Review* 102(3):47–52.

Bordalo, P., Gennaioli, N., and Shleifer, A. 2012b. "Salience theory of choice under risk." *The Quarterly Journal of Economics* 127(3):1243–1285.

Bordalo, P., Gennaioli, N., and Shleifer, A. 2013. "Salience and consumer choice." *Journal of Political Economy* 121(5):803–843.

Borgschulte, M., Molitor, D., and Zou, E. 2016. "Smoked out: The effect of wildfire smoke on labor market outcomes." Working Paper.

Bostwick, P., Menakis, J., and Sexton, T. 2011. "How fuel treatments saved homes from the 2011 Wallow fire." US Forest Service Fuel Treatment Effectiveness Assessement, Available online: `https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb5318765.pdf` [last accessed May 15, 2015].

Bucovetsky, S., Marchand, M., and Pestieau, P. 1998. "Tax competition and revelation of preferences for public expenditure." *Journal of Urban Economics* 44(3):367–390.

Bui, Q. and Sanger-Katz, M. 2016. "Why the government owns so much land in the west." *New York Times,* Available online: `https://www.nytimes.com/2016/01/06/upshot/why-the-government-owns-so-much-land-in-the-west.htm`.

Bureau of Land Management. 2014. "GeoCommunicator surface management agency dataset." Available online: `http://www.geocommunicator.gov/GeoComm/services.htm` [last accessed: August 26, 2014].

Cabral, M. and Hoxby, C. 2012. "The hated property tax: Salience, tax rates, and tax revolts." NBER Working Paper No. 18514.

Cameron, A.C. and Miller, D.L. 2010. "Robust inference with clustered data." Working paper series, Department of Economics, University of California, Davis, 10-7.

Canes-Wrone, B., Clark, T.S., and Kelly, J.P. 2014. "Judicial selection and death penalty decisions." *American Political Science Review* 108(1):23–39.

Carson, R.T. 2012. "Contingent valuation: A practical alternative when prices aren't available." *The Journal of Economic Perspectives* 26(4):27–42.

Center, N.I.F. 2017. "Suppression costs, 1985-2016." Available online: `https://www.nifc.gov/fireInfo/fireInfo_documents/SuppCosts.pdf` [last accessed October 19, 2017].

Chetty, R., Looney, A., and Kroft, K. 2009. "Salience and taxation: Theory and evidence." *American Economic Review* 99(4):1145–1177.

Conley, T.G. and Taber, C.R. 2011. "Inference with difference in differences with a small number of policy changes." *The Review of Economics and Statistics* 93(1):113–125.

Costello, C. and Polasky, S. 2008. "Optimal harvesting of stochastic spatial resources." *Journal of Environmental Economics and Management* 56(1):1–18.

DellaVigna, S. and Pollet, J. 2009. "Investor inattention and Friday earnings announcements." *The Journal of Finance* 64(2):709–749.

Dennison, P.E., Brewer, S.C., Arnold, J.D., and Moritz, M.A. 2014. "Large wildfire trends in the western United States, 1984–2011." *Geophysical Research Letters* 41(8):2928–2933.

Dessaint, O. and Matray, A. 2017. "Do managers overreact to salient risks? Evidence from hurricane strikes." *Journal of Financial Economics* 126(1):97–121.

Dewatripont, M., Jewitt, I., and Tirole, J. 1999. "The economics of career concerns, part II: Application to missions and accountability of government agencies." *The Review of Economic Studies* 66(1):199–217.

Diamond, P.A. and Hausman, J.A. 1994. "Contingent valuation: Is some number better than no number?" *The Journal of Economic Perspectives* 8(4):45–64.

Eidenshink, J., Schwind, B., Brewer, K., Z., Zhu, Quayle, B., and Howard, S. 2007. "Project for monitoring trends in burn severity." *Fire Ecology* 3(1):3–21.

Epanchin-Niell, R.S. and Wilen, J.E. 2012. "Optimal spatial control of biological invasions." *Journal of Environmental Economics and Management* 63(2):260–270.

Field, C.B., Barros, V., Stocker, T.F., and Dahe, Q., eds. 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, New York, NY.

Finkelstein, A. 2009. "E-ztax: Tax Salience and Tax Rates." *The Quarterly Journal of Economics* 124(3):969–1010.

Finney, M. 1998. "FARSITE: fire area simulator—model development and evaluation." USDA Forest Service Rocky Mountain Research Station, RMRS-RP-4.

Finney, M.A. 2002. "Fire growth using minimum travel time methods." *Canadian Journal of Forest Research* 32(8):1420–1424.

Finney, M.A., Grenfell, I.C., McHugh, C.W., Seli, R.C., Trethewey, D., Stratton, R.D., and Brittain, S. 2011. "A method for ensemble wildland fire simulation." *Environmental Modeling & Assessment* 16(2):153–167.

Franklin, J.F. and Agee, J.K. 2003. "Forging a science-based national forest fire policy." *Issues in Science and Technology* 20(1):59–66.

Freeman, A.M., Herriges, J.A., and Kling, C.L. 1993. *The Measurement of Environmental and Resource Values*. Taylor Francis for RFF Press, New York, NY.

Fry, J.A., Xian, G., Jin, S., Dewitz, J.A., Homer, C.G., Limin, Y., Barnes, C.A., Herold, N.D., and Wickham, J.D. 2011. "Completion of the 2006 National Land Cover Database for the conterminous United States." *Photogrammetric Engineering and Remote Sensing* 77(9):858–864.

Gallagher, J. 2014. "Learning about an infrequent event: Evidence from flood insurance take-up in the United States." *American Economic Journal: Applied Economics* 6(3):206–233.

Gilens, M. 2005. "Inequality and democratic responsiveness." *Public Opinion Quarterly* 69(5):778–796.

Gilens, M. 2011. "Policy consequences of representational inequality." In P.K. Enns and C. Wlezien, eds., "Who Gets Represented," pp. 247–86. Russell Sage Foundation, New York, NY.

Gonzalez, P., Battles, J.J., Collins, B.M., Robards, T., and Saah, D.S. 2015. "Aboveground live carbon stock changes of California wildland ecosystems, 2001–2010." *Forest Ecology and Management* 348:68–77.

Gorte, R. 2013. *The Rising Cost of Wildfire Protection*. Headwaters Economics.

Gradstein, M. 1993. "Rent seeking and the provision of public goods." *The Economic Journal* 103(420):1236–1243.

Grimes, M. and Esaiasson, P. 2014. "Government responsiveness: A democratic value with negative externalities?" *Political research quarterly* 67(4):758–768.

Gude, P.H., Jones, K., Rasker, R., and Greenwood, M.C. 2013. "Evidence for the effect of homes on wildfire suppression costs." *International Journal of Wildland Fire* 22(4):537–548.

Hakanson, E.K. 2010. *Fuels Management Policy and Practice in the US Forest Service.* Ph.D. thesis, The University of Montana, Missoula, MT.

Hanemann, W.M. 1994. "Valuing the environment through contingent valuation." *The Journal of Economic Perspectives* 8(4):19–43.

Hausman, J. 2012. "Contingent valuation: From dubious to hopeless." *The Journal of Economic Perspectives* 26(4):43–56.

Hochman, O., Pines, D., and Thisse, J.F. 1995. "On the optimal structure of local governments." *The American Economic Review* pp. 1224–1240.

Hossain, T. and Morgan, J. 2006. "... plus shipping and handling: Revenue (non) equivalence in field experiments on eBay." *Advances in Economic Analysis & Policy* 5(2).

Hsiang, S.M. and Narita, D. 2012. "Adaptation to cyclone risk: Evidence from the global cross-section." *Climate Change Economics* 3(02).

Janeba, E. and Wilson, J.D. 2011. "Optimal fiscal federalism in the presence of tax competition." *Journal of Public Economics* 95(11):1302–1311.

Jayachandran, S. 2009. "Air quality and early-life mortality evidence from Indonesias wildfires." *Journal of Human Resources* 44(4):916–954.

Jenkins, S.P. 1995. "Easy estimation methods for discrete-time duration models." *Oxford Bulletin of Economics and Statistics* 57(1):129–136.

Johnson, R.N. and Watts, M.J. 1989. "Contractual stipulations, resource use, and interest groups: implications from federal grazing contracts." *Journal of Environmental Economics and Management* 16(1):87–96.

Kalies, E.L. and Kent, L.L.Y. 2016. "Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review." *Forest Ecology and Management* 375:84–95.

Keane, R.E., Ryan, K.C., Veblen, T.T., Allen, C.D., Logan, J.A., Hawkes, B., and Barron, J. 2002. "The cascading effects of fire exclusion in Rocky Mountain ecosystems." In J.S. Baron, ed., "Rocky Mountain futures: An ecological perspective," pp. 133–152. Island Press, Washington, DC.

Keeley, J.E., Aplet, G.H., Christensen, N.L., Conard, S.G., Johnson, E.A., Omi, P.N., Peterson, D.L., and Swetnam, T.W. 2009. "Ecological foundations for fire management in North American forest and shrubland ecosystems." Available online: `http://www.treesearch.fs.fed.us/pubs/32483`.

Kelly, N.J. and Enns, P.K. 2010. "Inequality and the dynamics of public opinion: The self-reinforcing link between economic inequality and mass preferences." *American Journal of Political Science* 54(4):855–870.

Kennedy, M.C. and Johnson, M.C. 2014. "Fuel treatment prescriptions alter spatial patterns of fire severity around the wildland–urban interface during the Wallow Fire, Arizona, USA." *Forest Ecology and Management* 318:122–132.

Konoshima, M., Albers, H.J., Montgomery, C.A., and Arthur, J.L. 2010. "Optimal spatial patterns of fuel management and timber harvest with fire risk." *Canadian Journal of Forest Research* 40(1):95–108.

Kousky, C. 2014. "Informing climate adaptation: A review of the economic costs of natural disasters." *Energy Economics* 46:576–592.

Kousky, C., Olmstead, S., and Sedjo, R. 2011. "In harm's way: Homeowner behavior and wildland fire policy." In K.M. Bradshaw and D. Lueck, eds., "Wildfire policy: Law and Economics Policy," Taylor Francis for RFF Press, New York.

Landfire. 2014. "Landfire data products, U.S. Department of Interior, Geological Survey." Available online: `https://www.landfire.gov/viewer` [last accessed: July 30, 2017].

Lindsay, B.R. and McCarthy, F.X. 2015. "Stafford Act declarations 1953-2014: Trends, analyses, and implications for congress." Congressional Research Service, R42702.

Loomis, J. 2004. "Do nearby forest fires cause a reduction in residential property values?" *Journal of Forest Economics* 10:149–157.

McCarty, N., Poole, K.T., and Rosenthal, H. 2009. *Polarized America: The dance of ideology and unequal riches.* MIT Press, Cambridge, Massachusetts.

McCoy, S.J. and Walsh, R.P. 2014. "WUI on fire: Risk, salience & housing demand." NBER Working Paper No. 20644.

Mitchell, R.C. and Carson, R.T. 1989. *Using Surveys to Value Public Goods: The Contingent Valuation Method.* Resources for the Future, New York, NY.

Moeltner, K., Kim, M.K., Zhu, E., and Yang, W. 2013. "Wildfire smoke and health impacts: A closer look at fire attributes and their marginal effects." *Journal of Environmental Economics and Management* 66(3):476–496.

Monitoring Trends in Burn Severity. 2014. "MTBS burned area boundaries." Available online: `http://mtbs.gov/index.html` [last accessed May 11, 2016].

Moritz, M. 2017. Personal communication, October 17, 2017.

Moritz, M.A., Batllori, E., Bradstock, R.A., Gill, A.M., Handmer, J., Hessburg, P.F., Leonard, J., McCaffrey, S., Odion, D.C., Schoennagel, T., and Syphard, A.D. 2014. "Learning to coexist with wildfire." *Nature* 515(7525):58–66. URL `http://www.nature.com/nature/journal/v515/n7525/abs/nature13946.html`.

Naficy, C., Sala, A., Keeling, E.G., Graham, J., and DeLuca, T.H. 2010. "Interactive effects of historical logging and fire exclusion on ponderosa pine forest structure in the northern Rockies." *Ecological Applications* 20(7).

National Interagency Fire Center. 2016. "Total wildland fires and acres (1960-2015)." `https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html` [last accessed October 3, 2017].

National Wildfire Coordinating Group. 2017. "NWCG glossary." Available online: `https://www.nwcg.gov/glossary/a-z` [last accessed: July 24, 2017].

Nelson, R.H. 2017. "Give states control over public land out west." *The New York Times,* Published on January 11.

Niskanen, W.A. 1971. *Bureaucracy and representative government.* Transaction Publishers, New Brunswick, NJ.

Nunn, N. and Puga, D. 2012. "Ruggedness: The blessing of bad geography in Africa." *Review of Economics and Statistics* 94(1):20–36.

Osborne, M.J. and Turner, M.A. 2010. "Cost benefit analyses versus referenda." *Journal of Political Economy* 118(1):156–187.

Page, B.I., Bartels, L.M., and Seawright, J. 2013. "Democracy and the policy preferences of wealthy Americans." *Perspectives on Politics* 11(1):51–73.

Parisien, M.A., Snetsinger, S., Greenberg, J.A., Nelson, C.R., Schoennagel, T., Dobrowski, S.Z., and Moritz, M.A. 2012. "Spatial variability in wildfire probability across the western United States." *International Journal of Wildland Fire* 21(4):313–327.

Pateman, C. 1970. *Participation and democratic theory.* Cambridge University Press, Cambridge, UK.

Prendergast, C. 2007. "The motivation and bias of bureaucrats." *American Economic Review* 97(1):180–196.

Radeloff, V., Hammer, R., Steward, S., Fried, J., Holcomb, S., and McKeefry, J. 2005. "The wildland-urban interface in the United States." *Ecological Applications* 15(3):799–805.

Riley, S.J. 1999. "Index that quantifies topographic heterogeneity." *Intermountain Journal of Sciences* 5(1-4):23–27.

Ringquist, E.J. 2005. "Assessing evidence of environmental inequities: A meta-analysis." *Journal of Policy Analysis and Management* 24(2):223–247.

Romer, T. and Rosenthal, H. 1979. "Bureaucrats versus voters: On the political economy of resource allocation by direct democracy." *The Quarterly Journal of Economics* pp. 563–587.

Sabatier, P.A., Loomis, J., and McCarthy, C. 1995. "Hierarchical controls, professional norms, local constituencies, and budget maximization: An analysis of US Forest Service planning decisions." *American Journal of Political Science* pp. 204–242.

Samuelson, P.A. 1954. "The pure theory of public expenditure." *The Review of Economics and Statistics* pp. 387–389.

Sances, M.W. 2016. "The Distributional Impact of Greater Responsiveness: Evidence from New York towns." *The Journal of Politics* 78(1):105–119.

Schoennagel, T., Veblen, T., and Romme, W. 2004. "The interaction of fire, fuels, and climate across Rocky Mountain forests." *BioScience* 54(7):661–676.

Sexton, S. 2015. "Automatic bill payment and salience effects: Evidence from electricity consumption." *Review of Economics and Statistics* 97(2):229–241.

Short, K. 2017. "Spatial wildfire occurrence data for the United States, 1992-2015 [FPA_FOD_20170508]." Available online: `https://doi.org/10.2737/RDS-2013-0009.4`.

Stetler, K.M., Venn, T.J., and Calkin, D.E. 2010. "The effects of wildfire and environmental amenities on property values in northwest Montana, USA." *Ecological Economics* 69:2233–2243.

Sueyoshi, G.T. 1995. "A class of binary response models for grouped duration data." *Journal of Applied Econometrics* 10(4):411–431.

Taylor, S.E. and Thompson, S.C. 1982. "Stalking the elusive 'vividness' effect." *Psychological Review* 89(2):155.

Thompson, M.P. 2014. "Social, institutional, and psychological factors affecting wildfire incident decision making." *Society & Natural Resources* 27(6):636–644.

Thompson, M.P., Haas, J.R., Finney, M.A., Calkin, D.E., Hand, M.S., Browne, M.J., Halek, M., Short, K.C., and Grenfell, I.C. 2015. "Development and application of a probabilistic method for wildfire suppression cost modeling." *Forest Policy and Economics* 50:249–258.

Ura, J.D. and Ellis, C.R. 2008. "Income, preferences, and the dynamics of policy responsiveness." *PS: Political Science & Politics* 41(4):785–794.

US Census Bureau. 2000. "Census 2000 Summary File 3 Sample Data." Available online: `https://factfinder.census.gov/` [accessed March 26, 2018].

US Department of Agriculture. 2017. "Forests to faucets data." Available online: `https://www.fs.fed.us/ecosystemservices/FS_Efforts/forests2faucets.shtml` [last accessed July 25, 2017].

US Department of Agriculture and Department of Interior. 2001. "Urban wildland interface communities within vicinity of Federal lands that are at high risk from wildfire." *Federal Register* 66:751–777.

US Department of Agriculture and Department of Interior. 2009. "Guidance for implementation of federal wildland fire management policy." Available online: `https://www.nifc.gov/policies/policies_documents/GIFWFMP.pdf` [last accessed May 16, 2018].

US Fish and Wildlife Service. 2017. "Threatened & endangered species active critical habitat report." Available online: `https://ecos.fws.gov/ecp/report/table/critical-habitat.html` [last accessed September 6, 2017].

US Forest Service. 2017. "Fiscal year 2018 budget justification." Available online: `https://www.fs.fed.us/sites/default/files/usfs-fy18-budget-justification.pdf` [last accessed May 15, 2018].

US Government Accountability Office. 2016. "Federal disaster assistance: Federal departments and agencies obligated at least $277.6 billion during fiscal years 2005 through 2014." Report to Congressional committees, GAO-16-797.

USDA Office of the Inspector General. 2006. "Audit report: Forest Service large fire suppression costs." 08601-44-SF.

Van Der Werf, G.R., Randerson, J.T., Collatz, G.J., Giglio, L., Kasibhatla, P.S., Arellano, A.F., Olsen, S.C., and Kasischke, E.S. 2004. "Continental-scale partitioning of fire emissions during the 1997 to 2001 El Nino/La Nina period." *Science* 303(5654):73–76.

Verba, S., Schlozman, K.L., and Brady, H.E. 1995. *Voice and equality: Civic voluntarism in American politics*, vol. 4. Cambridge Univ Press.

Westerling, A., Hidalgo, H., Cayan, D., and Swetnam, T. 2006. "Warming and earlier spring increases western U.S. forest wildfire activity." *Science* 313(5789):940–943.

Westerling, A.L. 2016. "Increasing western US forest wildfire activity: Sensitivity to changes in the timing of spring." *Phil. Trans. R. Soc. B* 371(1696).

Whalley, A. 2013. "Elected versus appointed policy makers: Evidence from city treasurers." *The Journal of Law and Economics* 56(1):39–81.

Wibbenmeyer, M.J., Hand, M.S., Calkin, D.E., Venn, T.J., and Thompson, M.P. 2013. "Risk preferences in strategic wildfire decision making: A choice experiment with US wildfire managers." *Risk Analysis* 33(6):1021–1037.

Wilson, R.S., Winter, P.L., Maguire, L.A., and Ascher, T. 2011. "Managing wildfire events: Risk-based decision making among a group of federal fire managers." *Risk Analysis* 31(5):805–818.

Wlezien, C. and Soroka, S.N. 2011. "Inequality in Policy Responsiveness?" In P.K. Enns and C. Wlezien, eds., "Who Gets Represented," pp. 285–310. Russell Sage Foundation, New York, NY.

Wright, J.M. 2000. *The nation's responses to flood disasters: A historical account.* Association of State Floodplain Managers, Madison, WI.