Moral Hazard, Wildfires, and the Economic Incidence of Natural Disasters

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We measure the degree to which large government expenditures on wildland fire protection subsidize development in high risk locations. A substantial share of the total social costs of wildfires comes from federal firefighting efforts that prevent or reduce property loss. We assemble administrative data from multiple state and federal agencies to calculate, in great spatial detail and for the entire western United Status, the expected cost to the government of protecting at-risk homes from wildfire. To do so, we first measure the causal impact on firefighting costs when homes are built in harm's way. We then add up historical protection expenditures incurred on behalf of each home and calculate an actuarial measure of expected future cost. This measure is increasing in fire risk and surprisingly steeply decreasing in development density. In high-cost areas, the expected present value of fire protection exceeds 10% of a home's transaction value. We consider the potential for these subsidies to distort location choice, development density, and private investments in risk reduction.

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1 Introduction

Driven by a combination of climate change and expanding development in high-risk locations, annual wildland firefighting costs for the federal government have more than doubled in real terms over the past 30 years and are expected to continue to grow rapidly.[1] Every summer and fall, tens of thousands of men and women and many millions of dollars worth of equipment and aircraft are continuously dispatched throughout the western United States. Their costly, dangerous work is often explicitly targeted at preventing damage to private homes. While decisions about where and how to build these homes are largely made by localities and individual homeowners, the costs of defending them are mostly borne by the federal government.

This apparent misalignment of costs and benefits is due to the historical development of fire management and land ownership in the United States. While fire protection in cities has long been the responsibility of local governments, fire management for the huge public forests and grasslands that pervade the western part of the country is the task of the U.S. Forest Service (USFS) and other federal and sometimes state agencies. Rapid suburban and exurban home development starting in the second half of the 20th century increased the number of homes bordering these public lands (Radeloff et al. 2005; Radeloff et al. 2018). Because of the way financial and operational responsibility for firefighting is assigned, federal and state agencies are responsible for fighting most of the wildland fires that threaten these homes.

In addition to higher overall fire risk, the geographic variance of fire risk in these "wildland-urban interface" (WUI) areas is larger than within cities. Historical institutions for protecting urban homes did not disproportionately benefit particular property owners or neighborhoods, since urban fire risk is relatively homogeneous. In comparison, wildland fire risk is highly geographically differentiated according to topography, vegetation, and climate. Predictably high-risk areas suffer repeated, costly fires while lower risk places experience few or none.

The combination of publicly provided fire protection and large spatial heterogeneity in risk has two important implications. First, because the federal government bears the large majority of wildland firefighting costs, firefighting represents a transfer of wealth to a relatively small group of homeowners in locations with high fire risk.

[1] National Interagency Fire Center. "Federal Firefighting Costs (Suppression Only)". 2017.

Second, the guarantee of federal protection generates moral hazard. Homeowners do not internalize the expected costs of future fire protection when choosing where to live or how to design and maintain their homes. Perhaps just as importantly, local governments do not internalize firefighting costs when making zoning, land use, and building code decisions.

These uninternalized firefighting costs represent a major component of the total social cost imposed by wildfires. Wildfires are unusual among natural hazards in that it is feasible to prevent private property damage while an incident is ongoing through large investments of manpower and equipment. Unlike cyclones or earthquakes, for example, wildfires can often be "stopped in their tracks" to protect homes and other valuable assets. While tragic losses of life and property receive appropriately large attention, a large share of the costs imposed on society by wildfires come in the form of extremely costly efforts to prevent property damage. During 1985–2017, total wildfire property damages in the United States were $51 billion, while direct firefighting costs for federal agencies alone totaled $43 billion.[2] Public assistance for floods, cyclones, and other disasters comes in the form of rebuilding grants or insurance subsidies to individual households. Because wildfire spending comes in large part through firefighting expenditures, identifying the beneficiaries of that spending requires a more involved analysis that has not previously been undertaken.

In this paper, we quantify the economic consequences of America's wildfire institutions. We provide the first quantitative estimates of the implicit transfer to homeowners due to fire protection at the individual parcel level for homes throughout the western United States. To do so, we combine parcel-level data on the universe of single family homes in the West with administrative data on historical firefighting expenditures to estimate federal government expenditures dedicated to protecting each home from wildfires. We assemble the firefighting cost data from administrative records of six different federal and state agencies, which we obtained through multiple Freedom of Information Act and public records requests. This yields the most comprehensive dataset on wildland firefighting expenditures in existence. Our empirical approach takes advantage of variation in ignition locations to measure how incident-level firefighting expenditures increase when homes are built in harm's way. We then use these

[2]Values are in 2017 dollars. Damages are from Munich RE NatCatService and are overall losses (insured and uninsured) for wildfires and heat waves in the United States. Firefighting costs are from National Interagency Fire Center, "Federal Firefighting Costs (Suppression Only)".

estimates to construct an actuarial measure of the expected additional future cost to the government to protect each home from wildfires.

We find that residential development dramatically increases firefighting costs, to the point that efforts to protect private homes account for the majority of wildland firefighting expenditures. Perhaps more surprisingly, once development reaches a relatively low density threshold we find that further increases in the number or total value of threatened homes have little effect on firefighting costs. This non-rival aspect of fire protection means that development density is an important determinant of per-home protection cost. Overall, we find that firefighting represents a remarkably large transfer to a few landowners in high-risk, low-density places. In our highest-risk categories, the net present value (NPV) of fire protection costs exceeds 10+% of the transaction value of the property.

These large implicit subsidies imply potentially significant efficiency costs. We consider possible distortions along three margins. First, because the supply of new homes in high-cost areas is relatively elastic, there may be substantial distortions in new home construction in the highest fire-risk areas. Second, providing fire protection for free reduces incentives to capitalize on the economies of density that we measure, effectively subsidizing large lot sizes and low-density development. If sprawl is an independently undesirable outcome resulting from pre-existing market failures, this distortion could further exacerbate these inefficiencies. Finally, publicly provided fire protection may reduce private construction and maintenance investments that can protect homes. The promise of an aggressive firefighting response at no cost could reduce private incentives to choose fire-proof building materials and clear brush around homes, actions that can decrease the threat to homes during a wildfire. Similarly, aggressive federal firefighting limits the incentives for cities and states to create and enforce wildland building codes and defensive space regulations. These distortions could be mitigated through policies that lead individuals and localities to internalize a larger share of firefighting costs. We discuss several such policy interventions. We also explain how our empirical approach could be used to calculate an optimal fire protection fee that would lead developers or cities to internalize the expected future costs of firefighting imposed by new construction in currently undeveloped areas.

From a fiscal perspective, our results imply that wildland firefighting is a previously-unappreciated mechanism for redistribution to particular parts of the West. For example, we find that the annual implicit subsidies to homeowners in Montana and Idaho via firefighting are larger than federal transfers to those states under the Temporary Assistance to Needy Families (TANF) program.[3] Contrary to conventional wisdom, we do not find that federal fire protection spending is regressive. This is because fire protection costs are highest in rural and ex-urban parts of the West where incomes and land values are relatively low.

The importance of the issues we consider will continue to increase. Foresters and ecologists predict large amounts of new construction over the next several decades in fire-prone locations throughout the West that currently have no or very little development (Gude, Rasker, and Noort 2008). Mann et al. (2014) forecasts land use in California through 2050, and finds that predicted land use changes are dominated by the conversion of undeveloped or very sparsely developed areas to low- and medium-density housing use. Much of this new development is predicted to occur in areas that the state has designated as "very high" wildfire risk zones. At the same time, climate change is predicted to lead to more severe and more frequent wildfires.

More broadly, our results underscore the importance of institutions in responding to the impacts of climate change. Floods, cyclones, landslides, heat waves, droughts, and wildfires are all predicted to increase in frequency and severity as the Earth warms.[4] Many important adaptive responses to these and other impacts of climate change are likely to occur through government investments in public goods like infrastructure, national security, scientific research, public health, emergency response, and other areas. These large public investments may lessen the costs of climate change, but they also raise pressing economic questions about moral hazard, distributional impacts, and allocative efficiency.

Our analysis has specific parallels to flood risk, where economists have long suspected that subsidized federal flood insurance and ex-post rebuilding assistance may encourage high-risk development. Kousky, Luttmer, and Zeckhauser (2006), Smith

[3] Federal TANF expenditures in FY2016 were $32 million for Montana and $26 million for Idaho. U.S. Dept. of Health and Human Services, Office of Family Assistance, "TANF Financial Data - FY 2016", published February 2018. See sheet C.1.

[4] For a review of natural disasters and climate change, see IPCC, 2012: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, UK, and New York, NY, USA.

et al. (2006), and Boustan, Kahn, and Rhode (2012) consider the effects of floods and flood-related public policies on location decisions. Gregory (2017) studies the effect of federal rebuilding grants on homeowners' decisions to return to New Orleans following Hurricane Katrina. That study finds only modest distortions. In comparison to our setting, decisions about whether to rebuild a home in a place where one already lives seem likely to be less price-elastic than decisions about new development in currently undeveloped areas. Moreover, exposure to flood risk is mostly driven by the cross-city location decision about whether or not to remain in New Orleans. In the case of wildfire, we show that micro-scale within-region variation in risk and thus implicit subsidies is also important, increasing the potential for subsidies to distort decisions.

This paper makes several contributions. We demonstrate the importance of public defensive expenditures in lessening property damage from wildfires, and consider how this implicit subsidy affects incentives for private homeowners and local governments. Introducing novel administrative data on firefighting expenditures allows us to provide the first quantitative estimates of this implicit subsidy, and thus the optimal differentiated "fire protection fee", for every home in the western U.S. We also present novel estimates of the non-linear response of firefighting costs to the number of threatened homes, with important implications for the effect of freely-provided firefighting on development density. Finally, the introduction of parcel-level data on 18 million western homes allows us to be more geographically precise about risks and costs than existing studies, which rely on spatially coarse administrative boundaries. This specificity represents a valuable advance since fire and other disaster risks can vary substantially over small distances, as our results demonstrate.

The paper proceeds as follows. Section 2 provides institutional background on wildland firefighting. Section 3 establishes the economic context for our empirical analysis through a simple conceptual framework. Section 4 discusses the data. Section 5 and 6 present the empirical results. Section 7 considers efficiency costs along with policy alternatives to internalize fire protection costs. Section 8 concludes.

2 Wildland Firefighting in the United States

Wildland firefighting in the United States is provided by a patchwork of federal, state, and local government agencies. Broadly speaking, financial and operational responsibility is determined by a fire's ignition location. Fires that start on national forest land, for example, are the responsibility of the USFS. A handful of federal government agencies manage large amounts of public land and thus oversee significant firefighting activity in the West. In addition to USFS, these include the Bureau of Land Management, the National Park Service, the Bureau of Indian Affairs, and the Fish and Wildlife Service. Individual states also maintain large investments in wildland firefighting capacity and have primary responsibility for incidents on state-owned lands and private unincorporated areas. The largest state fire service is the California Department of Forestry and Fire Protection (Cal Fire). Incidents that start within the boundaries of towns and cities are initially the responsibility of local fire departments. Regardless of the managing agency, large incidents feature aid and cooperation across many different jurisdictions.

Many large wildfires that threaten homes begin on public land and are thus the financial responsibility of the federal (or sometimes state) government. The federal government also bears a portion of costs incurred on incidents "owned" by state and local governments through grants from the Federal Emergency Management Agency (FEMA). For qualifying large fire incidents, the FEMA Fire Management Assistance Grant (FMAG) program reimburses states and cities 75% of their firefighting costs. Through this combination of direct expenditures and indirect support, the federal government absorbs a large share of wildland firefighting expenses.

Wildland firefighting efforts have multiple objectives, among them safeguarding human lives, protecting natural resources and endangered species, and preventing damage to private property. Existing case studies and interviews indicate that protection of structures is disproportionately important in determining firefighting costs. It requires significantly more manpower and equipment (e.g., air support, bulldozers) to stop a fire in place before it reaches homes, as opposed to letting the fire burn out naturally at a road or ridge or other natural fire barrier. Forest Service personnel have speculated that between 50 and 95 percent of federal firefighting costs are due to efforts to prevent damage to homes (USDA, 2006). Case studies of small samples of fires have found econometric results in line with these estimates (Gebert, Calkin, and Yoder 2007; Liang et al. 2008; Gude, Jones, Rasker, and Greenwood 2013). Wibbenmeyer (2017) shows that fire perimeters coincide closely with areas of changing population and housing density, implying that fire managers frequently stop fires just before they reach more populated areas. The same study also finds that firefighting expenditures in many cases exceed the value of structures predicted to be threatened by a simulation model. This either indicates that firefighting dispatch is inefficient, or that managers consider additional values such as natural resources, the contents within homes, and the risk of catastrophic losses if the fire exceeds the forecast area.

The overall increase in wildland firefighting costs over the past several decades has been attributed to three factors: increased human habitation in fire-prone areas, the lengthening of the fire season as a result of climate change, and the buildup of increasingly dangerous fuel loads. Numerous descriptive studies in the forestry and urban planning literature document widespread, ongoing construction of new housing in high fire-risk areas (e.g., Radeloff et al. 2005; Gude, Rasker, and Noort 2008; Martinuzzi et al. 2015; Radeloff et al. 2018). Between 1990 and 2000, 8 million homes were added to the Wildland-Urban Interface, or WUI (Hammer, Stewart, and Radeloff 2009). At the same time, changes in climate affected the amount of fuel available for fires and the ease with which it burns. Climate change may be responsible for an additional 4.2 million acres burned between 1984 and 2015, accounting for nearly half of the increase in acres burned (Abatzoglou and Williams 2016).

The increase in available fuels is also due to forest management decisions. Land use change and a policy of fire suppression have altered the type and the extent of fuel availability in the Western United States (Stephens, Collins, Biber, and Ful 2016). Although the precise impacts of these changing fuels on the cost of fires is the subject of continuing scientific investigation, the majority view is that aggressive fire suppression efforts have led to an increased risk of large, damaging fires. Many ecologists argue that greater use of prescribed and managed fires would reduce the risk of dangerous wildfires and lower overall required expenditures on fire management. Efforts to implement these recommendations have proven politically unpopular and have been met with limited success.

The nuances of U.S. fire protection policy described in this section suggest an alternative approach to our research question, which is to attempt to measure changes in construction and home prices in response to changes in firefighting policy over time or at jurisdictional boundaries. An advantage of this approach is that it could yield direct reduced-form estimates of the effects of past policy changes on home development. At the same time, it has important limitations. We are not aware of any part of the U.S. where no effort is made to protect homes during wildfires, meaning such approaches will rely on small, difficult-to-interpret differences in perceived protection.[5] In comparison, our approach is more interpretable and generalizable. By using expenditure data to estimate implicit subsidy amounts, we recover an economic parameter that is directly useful for policy questions. Combined with estimates of supply and demand for new residential construction, our results can be used to calculate expected quantity changes and deadweight loss. Our estimates also directly reveal the fiscal and distributional consequences of federal firefighting policy. Furthermore, our estimates are calculated for the entire Western U.S., as opposed to the place and time of a particular policy change or boundary.

Another advantage of our approach is that it does not require us to assume that home buyers under the current regime are fully informed and rational about wildfire risk. Home prices in wildland areas have been shown to decrease after nearby fires or information campaigns about fire risk, suggesting this risk is imperfectly salient (Loomis 2004; Donovan, Champ, and Butry 2007; McCoy and Walsh 2014). Interpreting observed changes in prices and development in response to firefighting policy thus requires an assumption about salience. This approach requires not only that homeowners value possible losses from future fires (perhaps through shopping for homeowners insurance) but also that they perceive relatively minor *differences* in property risk when firefighting policy changes across time or boundaries. Moreover, many policy interventions (e.g., pricing firefighting) could themselves change risk salience, limiting the usefulness of reduced form estimates in guiding policy or calculating corrective taxes. In comparison, we do not require any assumptions about salience to calculate implicit subsidies. To evaluate potential policies, the required assumptions about salience are also relatively weak. To contemplate a policy where

[5] Even in the few remote areas with no local fire service ("no-man's land"), neighboring jurisdictions, states, and federal agencies can be expected to send resources when wildfires threaten homes. Furthermore, responsibility for firefighting is based on the ignition location (which is frequently federal public lands, prompting a federal response), not the location of homes eventually threatened.

developers pay an up-front fee equalling expected future protection costs, we need to assume that buyers correctly perceive this one-time, up-front tax payment (which the government calculates for them). In summary, we view our approach using expenditure data as more broadly relevant but also see reduced form evaluation of past policy changes as a complementary area for future research.[6]

3 Conceptual Framework

This section establishes the economic context for the parameters that we will estimate in the empirical analysis. We focus here on a stylized model. The primary goal is to illustrate how potential distortions in the housing market depend on 1) the relative magnitudes of defensive expenditures and expected property damages; 2) the severity of disaster risk; and 3) the elasticities of supply and demand for residential construction. The first of these is most interesting and is where we focus the discussion. We focus on location choice and development density, but the model could be extended to include private protective investments.

3.1 Setup

N households indexed by i choose to locate in one of two locations: "safe" (S) or "risky" (R). Each household weighs its (household-specific) benefit from each location against the location-specific cost of living, which includes the expected cost of a stochastic natural hazard (e.g., wildfire) and the price of a locally-produced non-tradable good (which we refer to as "housing" throughout this section). We impose several stylized assumptions that simplify exposition and allow us to focus on the elements of the model related to our research question. Households move frictionlessly between locations to maximize their utility. Regardless of location, households supply a single unit of labor inelastically a fixed wage and consume a single unit of housing at the local price. Housing is supplied in a competitive market. The risky and safe locations also vary in other (exogenous) amenities valued by households (e.g., outdoor

[6] The one relevant paper of which we are aware is a 2012 working paper showing that construction increased adjacent to federal lands after the 1988 Yellowstone fires prompted more aggressive firefighting policies (Kousky and Olmstead 2012).

recreation, restaurant quality). Each household's idiosyncratic taste for the amenities in the risky location (not including disaster risk) is θ_i.

The probabilities of a natural disaster in the risky and safe locations are ϕ and 0, respectively. Defensive expenditures f made in response to the disaster can reduce expected property damages to each individual resident, which we denote $H(f)$. Defensive expenditures (e.g., firefighting) are supplied by the central government. We make the following assumptions about f and $H(f)$, which are consistent with our data and stylized facts about natural disaster response.

1. $H'(f) < 0$ and $H''(f) > 0$. That is, defensive expenditures reduce expected damages, and do so with diminishing returns.

2. The benefits of defensive expenditures are non-rival within a location.

3. Within a location, homes are identical so that $H(f)$ is constant across homes.

In the event of a disaster, the government chooses the optimal level of defensive expenditure given population in the risky place, n_r. This value $f^*(n_r)$ minimizes the sum of defensive expenditures and total expected property damage, $f + n_r H(f)$.[7] $f^*(n_r)$ is increasing in n_r since, as population increases, more homes benefit from protection. In subsequent sections we drop the * for notational convenience.

3.2 The market for housing in the risky place

First consider the demand for housing under a policy that requires households to reimburse the central government for their proportional share of defensive expenditures after a disaster. In the absence of a disaster, realized household benefit from living in the risky place is, θ_i. If a disaster occurs, realized household benefit from living in the risky place is, $\theta_i - \frac{f(n_r)}{n_r} - H(f(n_r))$. The last two terms represent per-capita disaster costs. The sum of these two terms is decreasing in local population.[8] Assuming risk-averse households and perfectly competitive insurance markets, households in the risky place will purchase full insurance covering property losses and defensive expen-

[7]This rule mimics the principle of "least cost plus net value change" in the natural resources literature on fire suppression.

[8]This result comes from the envelope theorem, noting that $f(n_r)$ is chosen optimally to minimize disaster costs.

ditures. Premiums will equal expected losses, $\phi[\frac{f(n_r)}{n_r}+H(f(n_r))]$. Thus, the expected benefit of choosing to live in the risky location is $\theta_i - \phi[\frac{f(n_r)}{n_r} + H(f(n_r))]$.

Now consider an alternative policy where the central government does not require reimbursement for defensive expenditures. The expected disaster costs borne by households (and thus the households' insurance premiums) include only expected property damages, $\phi H(f(n_r))$. Accordingly, private net benefits from locating in the risky place are higher. The externalized costs of defensive expenditures are assumed to be borne equally by all households regardless of location through a constant budget-balancing tax equal to $\frac{1}{N}f(n_r)$.

Figure 1 depicts the market for housing in the risky location. The black downward sloping line shows demand for non-disaster amenities, θ_i. This line slopes downward due to heterogeneity in households' relative taste for the risky location. The solid gray line shows demand net of expected disaster costs $\phi[\frac{f(n_r)}{n_r} + H(f(n_r))]$. As discussed above, the vertical distance between these two lines is larger at lower population levels because per-capita disaster costs decrease with population. The dashed gray line shows demand net only of expected property damages, $\phi H(f(n_r))$, corresponding to the case where households are not required to pay for defensive expenditures. The black line labeled s shows the price of housing in the risky place. We assume that the marginal cost of housing in both locations is weakly increasing in population. This example is drawn to reflect elastic housing supply in the risky place up to a capacity constraint (perhaps due to land availability or regulation), followed by sharply increasing costs.

When households pay for defensive expenditures, the equilibrium population n_r^* equates demand and supply in the risky place such that $\theta_i - \phi[\frac{f(n_r)}{n_r} + H(f(n_r))] = s$. When the government pays for defensive expenditures, housing demand increases and population shifts to n_r'.

3.3 Implications for the empirical analysis

This analysis has three implications that we revisit in the empirical analysis. First, the share of the social costs of disasters that risky-place residents internalize depends on the relative magnitudes of defensive expenditures and property damages in the event of a disaster. When defensive expenditures make up a large share of total disaster costs, private location decisions ignore a large component of disaster costs. In our empirical application of wildland fire, defensive expenditures are an important share of total costs. Our empirical analysis yields novel, spatially-explicit estimates of $\phi\frac{f(n_r)}{n_r}$, directly quantifying this implicit subsidy.

The second implication is that the magnitude of disaster costs depends on the equilibrium population in the risky place. Per-capita disaster costs decrease with population, so that the marginal increase in *total* disaster-related costs from locating in the risky place is higher at low populations. Because we observe responses to a large number of wildland fire incidents in areas with varied population density, we are able to validate this feature of the model empirically. This result manifests itself importantly in our implicit subsidy calculations, where local housing density is an important predictor of expected per-capita protection costs.

Finally, the distortion in housing construction due to moral hazard depends on the elasticities of housing supply and demand. The increase in population is large when the housing market clears on the elastic portion of the supply curve. If instead demand intersects the inelastic portion of the supply curve, free provision of defensive expenditures has large effects on prices but little effect on quantities.

4 Data

We construct a dataset that combines administrative data on firefighting expenditures from federal and state agencies with assessor data from nearly all single-family homes in the western United States, defined as the states of Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming. In this dataset we also include topographical information, wildfire risk assessments, and weather conditions from the time and location of the fire ignition. In this section, we provide a high-level view of the dataset construction, while a comprehensive account of dataset construction can be found in Section B in the appendix.

We collect fire suppression and fire preparedness data from five federal agencies and one state agency. Fire suppression refers to expenditures made in the act of fighting a fire, while preparedness expenditures are costs incurred in order to reduce or mitigate damage from future fires. The five federal agencies from whom we collect data are the U.S. Forest Service (USFS), the National Park Service (NPS), the Bureau of Land Management (BLM), the Bureau of Indian Affairs (BIA), and the Federal Emergency Management Agency (FEMA). The state agency is California's Department of Forestry and Fire Protection (Cal Fire). Incident-level expenditures for each agency come from a combination of Freedom of Information Act requests (Public Records Act requests for California) and publicly available sources. Because fire costs are only reported consistently for large fires and because large fires comprise the bulk of fire suppression expenditures, we focus our analysis on fires that are 300 acres or larger. Our regression analysis in Section 5 focuses on the USFS fire suppression data, which cover 1995-2017. The calculation of implicit subsidies in Section 6 uses expenditures from all agencies.

For each fire, we use the location of the ignition point to obtain the topographical conditions at the fire (elevation, slope, aspect, and fuel model) as well as the weather conditions (temperature, precipitation, wind speed, and humidity) at the time of ignition. We also estimate the distance between the ignition point of each fire and valuable nearby resources, including homes and state and federal highways. We compute the number and value of homes within 5, 10, ..., 40 kilometers of the ignition point of each fire, as well as the distance from the ignition point to the nearest home.

The parcels dataset we use is a proprietary compilation of county assessor data provided by CoreLogic. It includes location, transaction values, year of construction, and other relevant property characteristics for 18.5 million parcels, or nearly all of the single family homes in the western United States. We limit this sample to 8.7 million homes in areas with significant wildland vegetation, as defined by Radeloff et al. (2018). For each home, our data includes a measure of its actual location, which is an improvement over previous papers about wildfire risk which rely on publicly available housing counts at the census block level. In the rural and ex-urban areas that make up the WUI, census blocks are often very large. Appendix Section B.2.1 includes more detail on these geographic data.

Our final dataset includes 7,430 fires that account for 11 billion dollars of suppression costs and links those fires using their location to the 8.7 million homes in the WUI. Table 6 lists descriptive statistics for these fires, and appendix Section B includes a comprehensive description of the dataset construction.

5 The Cost of Saving Homes During Wildfires

5.1 Empirical strategy

The first step in our empirical analysis is to establish what share of firefighting expenditures are incurred to protect private homes. Even in the absence of any nearby private home development, some amount of resources would likely be devoted to managing and suppressing a fire. Our objective is to understand how fire managers change the resources devoted to firefighting when homes are located in harm's way. This difference represents a subsidy to homeowners. We recover this difference empirically by estimating the casual impact of home presence and density on firefighting costs.

A number of observable and unobservable factors should be expected to affect the cost of fighting a fire, including ecological characteristics, local weather trends, and the typical response behavior of local fire managers. Our empirical strategy addresses this identification challenge by taking advantage of variation in ignition locations within U.S. national forests. Each of the national forests in our dataset experienced multiple large fires during our study period. We compare suppression costs for fires within the same national forest that happened to start at different distances from homes. Some fires start far away from private homes, for example deep inside the national forest, while other fires start nearer to homes, because the ignition point is closer to the national forest boundary or to a privately-owned "inholding", or because new homes have been built near the boundary. Figure 2 illustrates this variation for four example national forests. In each panel, the area of the national forest is shown in green. Fires are shown as x's and are colored by the distance from the ignition point to the nearest home. Fires that started more than 10 kilometers away from any home are shown in dark blue. Black markers indicate homes.

We take advantage of this variation in ignition locations using a fixed-effects estimation strategy. We model the effect of homes on fire suppression costs as,

$$ln(\text{Cost}_{ift}) = g(\text{Homes}_{it}) + X_{ift}\rho + \delta_f + \omega_{st} + \eta_{ift} \tag{1}$$

$Cost_{ift}$ is the suppression cost for fire i in national forest f in month-of-sample t. We are primarily interested in how this cost depends on the potential threat posed by the fire to private homes, Homes_{it}. We begin in Section 5.2 by parameterizing Homes_{it} as the distance from the ignition point of the fire to the nearest home. In Section 5.3, we consider the total number of homes near the ignition point. In either case, our preferred model approximates $g(\cdot)$ with a binned step function to allow a flexible response of costs to threatened homes (although our estimates are robust to a variety of functional forms).

This panel data approach addresses a number of omitted variables concerns. The national forest fixed effects δ_f control for unobservable determinants of firefighting cost that are constant at the national forest level. We also include time fixed effects ω_{st} that control flexibly for unobserved changes in firefighting costs over time. Our preferred specification includes state by month-of-year fixed effects and state by year fixed effects. Intuitively, this identification strategy amounts to comparing fires in the same national forest during the same time of year and the same year of the sample.

We include additional control variables X_{ift} to address the fact that locations of private homes are not randomly assigned. Even within a given national forest, areas near homes may differ systematically from areas far from homes in ways that affect firefighting cost. The control variables X_{ift} include the slope of the terrain at the ignition site, the geographic aspect, the vegetation type (fuel model), and weather conditions at the point of ignition on the ignition day.[9] We also estimate a specification where we limit the sample to fires caused by lightning, which ensures that the location and timing of fires is not driven by the presence of people. The identifying assumption in this analysis is that unobserved determinants of fire cost, η_{ift}, are independent of Homes_{it}, conditional on national forest fixed effects and our other controls.

5.2 Proximity to homes

We begin by considering a version of Equation 1 where the threat to private homes, Homes_{it}, is proxied by the distance from the ignition point to the nearest home that existed at the time of the fire. Figure 3 shows estimates from three flexible

[9] Only the weather conditions vary over time; elevation, slope, aspect, and fuel model are constant.

regression specifications. Each regression includes national forest fixed effects, state by month-of-year fixed effects, and state by year fixed effects. The solid black line shows the estimated marginal effect of distance from a regression of log costs on a cubic polynomial of distance to homes. The shaded gray area is the 95% confidence interval. The dashed black line shows a linear spline in distance to homes, with knots placed every 10 kilometers. Finally, the black dots report coefficients from a binned step function specification. These coefficients correspond to indicator variables for 5-kilometer bins of distance to homes. The omitted category is fires that start more than 50 kilometers from any home. Regardless of the functional form that we choose, there is a clear gradient in firefighting costs with distance. The relationship is steep, monotonic and close to linear. Relative to a fire that starts 45 kilometers from any home, the log cost of a fire less than five kilometers from homes is higher by about 2.25. Taken literally, these estimates imply that a fire that starts less than 5 km from homes would cost 75% less if there were no homes within 25 km, and 93% less if there were no homes within 40 km.[10]

Table 1 estimates alternative models using a binned specification. Column (1) follows the figure. Column (2) adds additional controls for pre-determined fire characteristics. As we show in the appendix, the signs and magnitudes of the included covariates match expectations. Firefighting costs are higher where the terrain slopes more steeply, reflecting difficulty of access. Costs also increase with wind speed on the ignition day, consistent with the importance of wind in fire spread. Vapor pressure differential (VPD) is a measure of atmospheric dryness, where higher values imply drier air; as expected, high VPD increases firefighting costs.[11] Costs are also higher for fires on south- or southwest-facing slopes, which receive additional sun exposure and thus tend to have more readily combustible vegetation. While we find that many of these covariates have meaningful effects on firefighting costs, including them in the regression has little effect on our estimated distance gradient.

The remaining columns show three robustness checks. Column (3) replaces the time fixed effects with more granular month-of-sample by state fixed effects, which allow

[10] These percentage changes are calculated using the binned specification. Halvorsen and Palmquist (1980) and Kennedy (1981) show that the percentage effect of an indicator variable in a semi-log regression can be approximated as $e^{\beta-0.5V(\beta)}-1$, where β is the regression coefficient.

[11] VPD is the deficit between the observed vapor pressure and the vapor pressure at the current temperature if the air were fully saturated with water. Meteorologists have shown VPD to be an important measure of dryness and predictor of fire severity (Anderson 1936; Seager et al. 2015).

for arbitrary shocks to firefighting costs in each month of the dataset in each state. These finer-grained time fixed effects absorb higher-frequency local cost fluctuations that might be caused by weather patterns or other factors. This alternative specification produces a similar distance gradient. Column (4) restricts the sample to fires started by lightning. Some types of human-caused fires are more likely to occur near populated areas, introducing a potential identification concern if fires due to arson or campfires or other causes vary systematically in their difficulty to extinguish. The locations of lightning strikes are plausibly random and thus purged of this potential bias. If anything, the estimated distance gradient is steeper when this restriction is applied, though the estimates are not different in a statistical sense. Column (5) restricts to fires occurring in timber areas, since developed areas are also less likely to be heavily wooded than more remote areas. As before, the estimated distance gradient steepens slightly under this restriction. This is consistent with our expectation that any omitted variables that might persist after our empirical design and control variables would bias our estimated effects downwards.

5.3 Total Number of Homes

The results in the previous section imply that the *presence* of nearby private homes strongly affects firefighting costs. In this section we consider how this effect varies with the *density* of development. To do this, we fix a radius around each fire and estimate a version of Equation 1 that parameterizes Homes_{it} as the total number of homes within that radius. We use a 30 kilometer radius in our baseline specification. The online appendix shows results for alternative radii.

Figure 4 shows results from a binned step function specification. The reference bin is fires with zero homes within 30 km, and the other bins evenly divide the remaining fires into deciles. The presence of just one to 31 homes almost doubles expenditures on a fire. Costs are further increasing over the first few deciles, up to about 100–300 homes. Beyond that costs change very little, even for fires threatening thousands or tens or thousands of homes. This strongly nonlinear relationship between cost and density is consistent with the assumption in the theoretical model that the benefits of wildland firefighting are locally non-rival, and the subsequent result that marginal protection costs are decreasing in population density.

One way to contextualize these results is to convert the numbers of homes in Figure 4 into conventional measures of residential density such as the number of homes per unit area. The area of a circle with radius 30 km is 2,826 km^2. Simply dividing by this area yields "gross" density. Land use planners typically work with *net* density, which measures land consumption per housing unit after subtracting out open space, parks, pasture, roads, and other land uses. For comparison to this standard measure, we calculate the average of the reported lot sizes for all homes within 30 km of the fire. The median net density across fires in the fourth non-zero bin, where costs level off, is 0.17 homes per acre.[12] Mann et al. (2014) define 5 tiers of residential density: sparse, low, medium, high, and very high. A value of 0.15 homes per acre is between the cutoffs for "low" and "medium".

5.4 Additional Results and Robustness Checks

In addition to the checks described above, we include a more detailed set of additional results and robustness checks in the online appendix, which we describe here in brief. First, we show that the estimated density effects in Figure 4 are robust to the same checks shown in Table 1, such as limiting to lightning-caused fires or including finer-grained time fixed effects. We also show that using the total transaction value instead of the number of nearby homes yields similar results. Furthermore, we show that the implied marginal effect of homes on fire costs depends intuitively on the radius within which we count homes, where smaller radii imply larger per-home marginal effects, but that the strong non-linear response of costs to number of homes exists for any reasonable choice of radius.

Our measure of valuable structures threatened by a fire does not include public infrastructure such as school buildings and municipal parks that would also be considered by incident commanders when choosing response levels. This means that our approach assigns the cost of protecting those public goods to nearby homeowners. For

[12] This calculation is meant to provide broad context as opposed to a highly accurate measure of net density. We calculate the mean lot size within 30 km of each fire, and then calculate the median average lot size in each decile bin in the figure. These range from 0.11 homes per acre in the left-most non-zero bin to 1.01 homes per acre in the right-most bin (a "high" level of density following Mann et al. (2014)). The average lot size within 30 km of each fire is sensitive to some very large reported parcels. Lot size is also missing for some homes, which we necessarily omit from this calculation.

local public goods such as schools and parks, this makes intuitive sense, since construction of such local public goods follows as a direct result of housing construction (Brueckner 1997). It should also be noted that built structures in the WUI areas where we are focused are disproportionately residential, with residents who travel by car to more-developed commercial areas for shopping, work, and school.

Since firefighting costs are only consistently reported for incidents larger than 300 acres, a potential concern is bias due to sample selection. Our analysis could be affected if the subset of ignitions that reach this size differs with distance from homes in a way that is correlated with suppression costs. For example, one might worry that concentrated initial attack efforts near homes make ignitions near homes unlikely to grow large unless conditions are difficult (e.g., high winds). This selection would result in an upward bias in a naive regression of firefighting costs on distance to homes.[13] Importantly, we are able to control directly for the most significant potential confounders. Wind, weather conditions, and topography are primary determinants of suppression difficulty and cost (Gebert, Calkin, and Yoder 2007). Table 1 and Appendix Table 1 show that controlling flexibly for these variables improves the model fit while introducing only small changes in the coefficients of interest. This implies that sample selection or other omitted variables problems related to suppression difficulty are unlikely to affect our estimates. As an additional robustness check in the online appendix, we implement a parametric correction for sample selection and find similar estimates to those in the main text.

Because our baseline estimates are not suitable to consider the impact of homes on the *frequency* of fires in an area, we conduct a separate analysis to investigate how this might impact our findings. As some wildland fires are ignited by humans, increased human population may create more ignitions. On the other hand, new homes could be accompanied by greater fire prevention efforts. We explore this relationship using panel variation in new home construction near each of the national forests in our federal sample. We find weak evidence of a small positive effect of new home construction on the number of large fires each year in places that start from a low level of development. Adding an additional 1,000 homes in a relatively undeveloped area is associated with about a 3.5% increase in the number of fires each year, or

[13]Selection could in principle also occur in the other direction: Incident managers may respond more slowly to fires near homes when they pose little threat.

about 0.06 additional fires per year. The finding that human presence increases fire frequency is consistent with work by ecologists and geographers (Syphard et al. 2007; Massada, Syphard, Stewart, and Radeloff 2012; Faivre, Jin, Goulden, and Randerson 2014; Balch et al. 2017). This implies that our estimates may slightly undercount the additional firefighting cost created by new homes.

6 The Implicit Subsidy To Homeowners

This section calculates geographically-differentiated implicit subsidies due to wildland firefighting. For every individual home in the western United States, we calculate an actuarial ("ex-ante") measure of the expected net present value of the cost incurred by the federal and state governments to protect the home during wildfires. Section 6.1 describes the methods that we use to estimate historical ("ex-post") and expected ("ex-ante") protection costs for each home. Section 6.2 summarizes the estimated costs and demonstrates the relationship between observable risk predictors and realized protection costs. Section 6.3 describes the geographic incidence of these implicit subsidies at regional and local scales, and Section 6.4 describes the incidence according to income.

6.1 Methods to calculate realized and expected protection costs

6.1.1 Calculating historical federal firefighting expenditures

We begin by estimating the historical federal direct expenditures on firefighting attributable to each home. In brief, we calculate expenditures for home protection on each historical fire, allocate those costs to homes near the ignition point, and then sum up the costs assigned to each home. This section describes each of those steps.

In Section 5 we limit the dataset to USFS fires in order to take advantage of variation of fire ignition location within national forests. When calculating historical firefighting costs, we also include expenditures from BLM, NPS, and BIA in order to more fully capture federal agency expenditures.[14] For each fire, we use the estimated model in Equation 1 to predict the firefighting cost for the incident if there had been no homes within 45 kilometers of the ignition point. For each fire i we calculate the difference between the observed firefighting cost and this predicted counterfactual cost Δ_i.[15]

For each fire, we allocate Δ_i over homes within a fixed radius of the ignition point that were potentially threatened by the fire. Our definition of potentially threatened homes includes homes located within 45 km of the ignition point in areas with wildland vegetation. This vegetation classification follows Radeloff et al. (2005) and is described in detail in the appendix. Within the set of homes potentially threatened by each fire, we allocate Δ_i to homes using two sets of weights. First, we use inverse-distances weights, where threatened homes are assigned weights equal to the inverse of the distance $1/d$ between the home location and the fire ignition location, normalized to one within each fire, and home protection expenditures by fire are divided using the normalized weights. Our second and preferred set of weights uses the estimated proportional change in suppression cost from Equation 1 for the distance between the ignition point and the parcel location, normalized to sum to one for each fire. This exercise divides Δ_i across j potentially threatened homes, yielding costs δ_{ij} (calculated in 2014 dollars) for each home, where $\sum_{j=1}^{J} \delta_{ij} = \Delta_i$.

The next step of this calculation sums up the total costs associated with each home during 1995–2014. For each home j, we sum that home's costs for each fire during the study period, $\rho_j = \sum_{i=1}^{I} \delta_{ij}$. We call this quantity the *realized protection cost* for home j because it represents the amount of firefighting expenditure associated with the home during the study period.

6.1.2 Calculating ex-ante expected federal firefighting expenditures

The estimate of interest in the conceptual model in Section 3 is not ex-post realized expenditures, but ex-ante expected expenditures. The observed history of firefighting costs is 20 years or less, which in many regions may not be a long enough period to fully describe the underlying fire risk. To estimate expected firefighting costs,

[14] These additional data sources add a total of 93 million dollars (2017$) per year, compared to 486 million dollars per year for USFS.

[15] See Appendix Section B.3 for the construction of Δ_i.

we group regions with similar ecological and fire risk characteristics together into actuarial groups, much like private insurers do when calculating risk. We calculate expected cost for homes in each group as

$$\underset{h,d,s}{\mathbb{E}}\left[\rho_j\right]$$

This calculation takes expectations over bins of wildfire hazard h, development density d, and geographic region g. Wildfire hazard is defined at the parcel level using the spatially-explicit wildfire hazard potential scores provided by Dillon (2015), which are a physical measure of wildfire risk taking into account ecological and geological factors.[16] Development density (population per square meter) comes from the Gridded Population of the World dataset, which reports population density within 1 km grid cells. We define geographic regions based on the boundaries of the seven Geographic Area Coordinating Centers (GACCs) that coordinate regional firefighting operations in the West. This binning process results in 210 actuarial groups, each of which includes at least 1,000 homes. To reflect the ongoing nature of the firefighting guarantee, we calculate the net present value of the expected annual costs for each group of homes. We call this quantity the *expected parcel protection cost*. It represents the present value of the expected government expenditures for fire protection associated with each home.

In the online appendix, we present results from an alternative approach using machine learning techniques. Instead of choosing the actuarial groups ourselves, this approach uses a random forest estimator to define groupings based on wildfire hazard potential, population density, and geographic region that minimize the resulting mean square prediction error.

6.1.3 Incorporating additional expenditure categories

Governments incur additional firefighting expenses beyond direct expenditures by federal agencies. To reflect this, we calculate several different measures of protection cost that incorporate successively broader categories of costs. Each of these measures represents a tradeoff between completeness and strength of required assumptions. A

[16] The appendix includes more information on this physical risk measure as well as a map of wildfire hazard potential.

"suppression only" measure includes direct firefighting costs by USFS, BLM, NPS, and BIA. This measure requires the fewest assumptions beyond those in Section 5.1, but omits potentially important categories of expenditures. A "suppression plus" measure also accounts for the annual fixed costs of maintaining response capabilities ("preparedness" expenditures), and federal reimbursements to state and firefighting agencies through the Fire Management Assistance Grant (FMAG) program. Finally, our third measure is specific to California, the largest state in the West and a state where we have detailed state-level expenditure data.

The first element that we add to the "suppression plus" measure is federal preparedness spending. Allocating preparedness spending to individual fires involves two challenges, one conceptual and one computational. Conceptually, it is not clear how these annual costs should be attributed to individual incidents. We choose to divide preparedness costs equally across ignitions.[17] After this even division, we then calculate the share of preparedness costs due to homes using the same model as for suppression expenditures.[18] The computational challenge arises because of the large number of ignitions in the dataset. Actually allocating costs to every ignition would require us to calculate distances to homes and other detailed spatial analyses for 100,000+ ignitions. As a feasible alternative, we impose the strong assumption that the geographic distribution of ignitions is approximately similar to the geographic distribution of fires exceeding 300+ acres. Under this assumption, we can achieve the same spatial allocation of preparedness costs by allocating preparedness spending across large fires only. This procedure yields an amount of preparedness spending for each fire that can be attributed to homes. Finally, we allocate these per-fire costs across nearby homes using the same distance weights used for suppression spending.

The "suppression plus" measure also includes FEMA reimbursements to states and cities for wildfire firefighting costs. We take all wildfire-related incidents from FEMA and aggregate them to the state-year given for each. We then assign state-year FEMA spending to parcels using the same method given for the preparedness spending.[19] As

[17]For USFS, we divide each region-year of preparedness spending across fires in that region-year. The DOI agencies only report preparedness spending at the annual level, so we divide annual costs by annual number of fires.

[18]This assumes that homes increase preparedness costs by the same factor that they increase firefighting costs. While this is a strong assumption, we feel it is preferable to the other obvious alternative, which would be to assume that all preparedness costs are incurred to protect homes.

[19]This reflects the assumption that the spatial distribution of state and municipal fires reimbursed

with direct firefighting expenditures, we first calculate historical realized "suppression plus" expenditures, and then take expectations over similar-risk homes to calculate ex-anted expected costs.

6.1.4 A separate cost measure for California

Our final measure focuses on California, the largest and most populous state in the West. In this scenario, we exclude FEMA reimbursements to California and instead include Cal Fire suppression costs as a more granular measure of state expenditures. The incident-level Cal Fire data include geographic coordinates as well as costs, so we are able to allocate these suppression costs in the same way that we allocated USFS and DOI suppression costs in the "suppression only" scenario. This final measure is the most complete estimate of the implicit subsidy from wildfire firefighting that we can calculate with our data.[20]

6.2 Results: Implicit Subsidy Magnitudes

Figure 5 plots conditional means for historical protection costs. The figure shows average fire protection costs for homes in each of 400 bins. The sample of homes in this figure includes all 8 million homes in the western U.S. located near areas of wildland vegetation (about 47% of all western U.S. homes). This figure uses the "suppression plus" cost metric (similar figures using the other cost metrics are included in the online appendix). The color scale indicates the average protection costs for homes in each cell, according to a log scale. The range of historical protection costs is large. The average net present value of historical protection costs is a few hundred dollars per home for the lowest-cost cells and over $100,000 per home in the highest-cost cells.

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by FEMA fires matches the federal distribution. This assumption is unlikely to hold at the local level, meaning that the implicit subsidy represented in this scenario will misallocate the costs of state and municipal wildfires.

[20] Even this estimate fails to capture municipal spending and other publicly funded costs of wildfires. An example of this latter cost includes the expenditures by electric utility companies who are required to spend millions of dollars per year trimming trees near power lines in order to mitigate the risk of wildfire while delivering power to homes built in high-risk areas. Because these costs are effectively borne by all ratepayers, this too would constitute part of the implicit subsidy.

Moreover, there is a clear graphical relationship between realized protection costs and observable predictors of risk. The vertical axis is defined by 20 bins of landscape fire risk based on wildfire hazard potential, or WHP(Dillon 2015). WHP is a measure of physical fire risk based on vegetation, terrain type, and other landscape characteristics. Average protection costs are clearly increasing with WHP scores. This relationship is intuitive, but the magnitude of the cost difference between low- and high-WHP homes is striking. Along the horizontal axis, protection costs are strongly decreasing with development density. This somewhat more surprising result is likely due to the nonlinear relationship between firefighting costs and housing density that we documented in Section 5.3. Instead of being driven purely by idiosyncratic risk, the costs of protecting homes from fires appear to vary in a highly predictable way. Throughout the West, homes in low-density, high-fire-risk areas are extremely expensive to protect.

Table 2 describes the "expected protection costs" that result from aggregating homes into less granular actuarial groups, as described in 6.1.2. The first three columns describe the upper half of the distribution of the expected present value of firefighting costs due to each home, using three different cost measures. Using the "suppression only" measure, most western homes have expected protection costs of several hundred dollars or less, while the highest-risk homes have costs that are much larger. Five percent of homes have expected costs exceeding \$3,500. One percent of homes have expected protection costs exceeding \$11,500. Using the "suppression plus" measure results in higher costs. The 95th- and 99th percentiles of this distribution are about twice as high as for the "suppression only" measure. When we restrict the sample to California homes, where we have higher-quality data on state-level expenditures, we find that the 95th and 99th percentile costs are roughly similar to the previous column.

The right-hand column of Table 2 reports the "suppression plus" measure as a share of the transaction value of the property.[21] These implicit subsidies are large compared to housing values. For the 5% of homes with the highest relative costs, the present value of expected future firefighting costs is more than 5.1% of property value. For the highest 1% of homes, it exceeds 18%.

[21] We exclude some missing or unusable transaction values from this relative cost calculation, as described in the online appendix. For this table, we assign each home the average relative cost among homes in its actuarial group.

The expected costs in Table 2 are calculated by averaging together the experiences of groups of homes in different locations with similar risk characteristics. This means that the expected cost metrics do not simply reflect an unlucky or exceptional fire history in one small location. Instead, they represent the aggregate cost history of all homes in a given actuarial category. The homes at or above the 95th percentile in Column (2) represent 61 actuarial groups, while homes above the 99th percentile represent 18 actuarial groups.[22]

6.3 Results: Geographic Incidence

Figure 6 shows the broad geographic distribution of expected protection costs. This map shows the average expected protection cost for homes in each 15 kilometer hexagonal cell. The color scale corresponds to increasing costs. The scale is top-coded, so that the darkest red corresponds to homes with expected protection costs of $30,000 or more. Average expected protection costs are highest in Northern California, central Oregon and Washington, and Idaho and western Montana. These are all sparsely-populated areas with many areas of high fire risk.

The costs of protecting homes are a surprisingly large part of the bundle of federal benefits provided to households in these areas. To contextualize our findings, the annual implicit subsidies to homeowners in Montana and Idaho via firefighting are larger than federal transfers to those states under the Temporary Assistance to Needy Families (TANF) program.[23] Notably, Southern California, which also features high fire risk and frequent costly fires, has somewhat lower expected protection cost than these other regions. This likely reflects greater development density in fire-prone parts of Southern California, which reduces per-home firefighting costs.

Significant local variation in wildfire risk and development density in the West means that expected protection costs also vary substantially over small distances. Figures 7A and 7B illustrate this local variation for two areas in California. These maps show

[22] In the most geographically concentrated actuarial group, the distance between the two furthest-apart homes is 285 kilometers. In 95% of actuarial groups, the maximum distance between homes exceeds 567 kilometers. The online appendix describes alternative approaches to defining actuarial groups using machine learning methods.

[23] Federal TANF expenditures in FY2016 were $32 million for Montana and $26 million for Idaho. U.S. Dept. of Health and Human Services, Office of Family Assistance, "TANF Financial Data - FY 2016", published February 2018. See sheet C.1.

the net present value of per-home expected protection costs, averaged at the Census block level for plotting. Figure 7A shows Shasta county in Northern California. Expected protection costs are several hundred dollars per home or less in the more densely-developed areas of central Redding and Anderson. Outside of these urban areas, wildfire hazard increases and density decreases rapidly. As a result, expected protection costs are much higher. In some of the more remote Census blocks that border national forest lands or other public wildlands, costs are tens of thousands of dollars per home. These areas have a high underlying physical risk of fire, meaning that homes built here are likely to repeatedly require costly firefighting efforts to avoid destruction. In addition, these areas include fewer total homes, raising the per-home cost of firefighting. Figure 7B shows San Diego County in Southern California. Again, fire protection costs per home are low in the densely developed areas of San Diego, and increase in the high fire-risk, low-housing-density areas that border federal- and state-owned lands in the eastern part of the County.

6.4 Results: Incidence across Income Groups

Figure 8 explores the distributional effects of firefighting expenditures. A frequently-repeated claim about wildfire suppression in the United States is that it primarily benefits the rich (see, for example, "A Case for Letting Malibu Burn" (Davis 1995)). Our data tell a different story. Panel C shows that on average, homes in low-income areas of the West receive substantially more benefit from government firefighting efforts than homes in high-income areas. This likely reflects the fact that the areas with the highest per-home expected protection costs are low-density rural and semi-rural areas. Panel D considers an alternative measure of wealth, which is the transaction value of the home. For most American homeowners, the asset value of the home is a strong predictor of overall wealth. Again, the highest protection costs on average are associated with low-value homes. The data suggest a slight U-shaped relationship, such that average costs may be increasing for the very highest-value homes. This could reflect targeted government efforts to protect high-value homes during wildfires, or high-value second homes located in resort areas where permanent residents have low incomes.

7 Discussion

This section considers the economic implications of the large and widely-varying implicit subsidies that we identify. Section 7.1 considers the implications for economic efficiency, including location choice for new construction, lot size and development density, and private risk-reducing investments. Section 7.2 discusses potential policy interventions aimed at internalizing these costs.

7.1 Economic Efficiency

The welfare costs of this subsidy depend on the degree to which it distorts economic decisions. In this section we use our estimates to consider potential effects along several margins of interest. First, we consider the extensive margin choice by a municipality to allow new development or by an individual to build a new home in a high-risk area. Next, we consider questions related to lot size and development density. Finally, we consider private choices about risk-reducing activities such as maintaining vegetation and using fire-proof building materials.

7.1.1 New Development in High-Risk Areas

Mann et al. (2014) predicts that under a business-as-usual scenario, the dominant pattern of land use change in California through 2050 will be the conversion of undeveloped or very sparsely developed areas to low-density housing use, and that much of this development will be in high fire risk areas. Gude, Rasker, and Noort (2008) predicts similar conversion of undeveloped areas to housing on WUI lands throughout the West. To what degree is this land use change driven by freely-provided public fire protection? As illustrated in Section 3, the effects depend on the magnitude of per-capita protection costs and the elasticities of supply and demand for residential construction. Where demand and/or supply are highly inelastic, subsidized fire protection will have little effect on quantities. Instead, the subsidy will increase the prices of homes relative to a counterfactual where homeowners reimburse the government for firefighting costs. Housing supply in many urban centers in the West, especially California, is thought to be relatively inelastic due to land constraints and regulation

(Saiz 2010; Glaeser and Gyourko 2018).

In the low-density ex-urban and rural areas where we measure large implicit subsidies, existing research and standard urban economics reasoning suggests that supply is quite elastic. Development in these areas is generally not limited by land availability or regulation. Saiz (2010) reports supply elasticities in the metropolitan statistical areas (MSA) around Denver, Colorado Springs, and Albuquerque of 1.53, 1.67, and 2.27, respectively. This includes more urban parts of the MSA and thus may understate supply elasticities in wildland-urban interface areas. As further evidence of elastic housing supply, we observe that home prices in our highest-subsidy areas are low, near the minimum profitable construction costs presented in Glaeser and Gyourko (2018). These seem to be areas where homes are built and sold at close to their marginal construction costs. In these settings the standard assumption of perfectly elastic long-run housing supply is likely reasonable.

The local elasticity of demand is more difficult to capture precisely. The housing market response to prices includes long-distance migration, within-city location choice, and effects on household formation. Existing research offers a range of estimates for these various margins. For cross-city location decisions, Albouy (2009) uses a strikingly large price elasticity of -6.0, following Bartik (1991) and the author's own calculations. Kennan and Walker (2011) find that this value is smaller, about -0.5. For the within-city decision about whether to locate on the urban periphery or in the city center, Voith, Brueckner, and Holtz-Eakin (2000) use an elasticity of -0.5. Anas and Chu (1984) find a within-city location choice elasticity of between -0.27 and -0.87. Polinsky and Ellwood (1979) and Muth (1971) both find that the price elasticity of demand for new, detached single family housing is about -1.0. Collectively, these estimates suggest that -1.0 might be a conservative estimate of the overall elasticity of new housing demand with respect to price in high fire-risk regions.

In the spirit of Harberger (1964), if we assumed no other distortions and perfectly elastic housing supply, we could calculate the deadweight loss in each of our actuarial groups j as $\frac{1}{2}\eta_j Q_j p_j (\frac{\tau_j}{p_j})^2$, where η_j is the compensated demand elasticity for new residential housing, Q_j and p_j are the quantity and average price of single family homes, and τ_j is the expected protection cost for homes in group j. Implementing this calculation using a value of -1.0 for η in all groups yields an aggregate deadweight loss of \$690 million dollars in net present value. This figure is driven by large deadweight loss per dollar of subsidy expenditure in regions with the highest expected protection cost. The online appendix shows calculations using different elasticities, including a less elastic housing response in denser areas such as Southern California.[24]

This benchmark approximation based on the simple framework in Section 3 abstracts away from some complications. One is that home buying in the United States is also subsidized through the income tax code, as studied by Poterba (1992) and others. The existence of this additional subsidy to housing likely increases the deadweight loss associated with free provision of wildland firefighting.

7.1.2 Development density and lot size

Our calculations in Section 6 construct the average expected cost of protecting a home from fires. This is the relevant quantity for understanding per-capita transfers to homeowners and the external cost of new development in currently undeveloped areas. However, in areas with existing development, the marginal costs of new development differ from this average cost. Figure 4 shows that beyond net densities of roughly 0.17 homes per acre, expenditures on firefighting increase little with additional development. The degree to which per-capita fire protection costs decrease with density is one of the more surprising results in this study. This result suggests that protection from fires is non-rival: at medium and high densities, adding additional homes in the path of a fire does not seem to decrease the protection enjoyed by those already there. These economies of scale in fire protection imply cost savings from denser development. Providing fire protection for free removes the incentive to consider these economies, effectively subsidizing low-density development patterns.

Given the durable nature of housing, our protection costs are not high enough to justify abandonment of already-constructed homes. Thus, if a policy were implemented today that charged all new homes the marginal fire protection cost for their area, we would expect more "infill" construction in already-developed areas (relative to a regime with unpriced fire protection). To the extent that such "densification" is seen as an independently desirable outcome because of other market failures affecting land

[24]Because the largest per-capita subsidies are in rural and ex-urban areas, the choice of elasticity for densely populated areas has a relatively small effect.

use, pricing fire protection may have additional benefits. Economists have identified market failures like congestion externalities that contribute to urban sprawl, while also recognizing that urban expansion reflects fundamentals like population growth and technological change (Brueckner 2001; Glaeser and Kahn 2004).

7.1.3 Private risk-reducing investments

In addition to changing incentives about where to build, free firefighting may affect incentives about how to build and maintain homes. A number of decisions during construction can reduce a home's risk of damage during a wildfire, at some cost (either monetary or aesthetic). For example, homes can be built with highly fire-resistant roofing and other materials. Once the home is built, residents can protect the home by trimming vegetation around the home to create "defensible space". If these investments reduce the level of firefighting dispatch required to protect the home in the event of a fire, providing firefighting for free will lead to underinvestment in these partial substitutes.

Researchers report that many homeowners in WUI areas fail to create adequate defensible space around their homes, despite widespread outreach efforts by fire officials (Champ, Donovan, and Barth 2013; Dickinson, Brenkert-Smith, Champ, and Flores 2015). Underinvestment in self-protection could reflect frictions like imperfect information about risk or behavioral failures by homeowners. The substantial financial incentives that we identify in this paper are another possible explanation for lowered takeup of these investments. One suggestive fact from our own data is that the share of homes with wood roofs is similar across actuarial groups regardless of expected firefighting cost. Local governments can mandate self-protection through building codes and vegetation inspections. However, their incentive to implement and enforce such regulations is lowered by the large share of firefighting costs shouldered by the federal government. We see further study of private and municipal investments in risk mitigation as an important area for additional research.

7.2 Policy Alternatives

Economic reasoning suggests that these potential distortions could be reduced by policies that internalize wildland firefighting costs. One possibility is to require homebuilders to pay a fee equal to the net present value of expected protection costs when building a new home in a currently-undeveloped area. This policy leads homeowners to internalize firefighting costs in expectation. Moreover, our empirical analysis provides a road map for calculating this spatially-specific optimal corrective tax. In 2014, California took a small step in this direction by requiring homeowners in the Cal Fire protection area to pay an annual fee of about \$150 per year. The fee was unpopular in rural areas and was suspended in 2017. Our results suggest that such a fee would need to be much more geographically differentiated in order to correct incentives (as opposed to simply raising revenue for firefighting).

The same objective could be achieved by recovering ex post firefighting costs directly from insurers holding homeowners insurance policies near the ignition point of a fire. Such a policy would increase insurance premiums according to expected firefighting costs. In order to be effective, this policy might need to be coupled with a mandate that homeowners purchase insurance.

An alternative policy is to assign a larger share of the costs of fire protection to local governments, which would recover these costs through property taxes or other taxes. One potential advantage of this approach is that it would incentivize cities and counties to consider firefighting costs in zoning and land use decisions. In principle, one could imagine that the existing federal firefighting system could continue to supply firefighting, while collecting payment from cities and counties for this service.

8 Conclusion

Unlike other types of natural disasters, a large share of the total social costs of wildfires are represented by emergency response costs as opposed to property damage. The federal government spends billions of dollars each year fighting wildfires. We find that efforts to protect private homes account for the large majority of this spending. This means that homeowners and municipalities in high-risk locations do not internalize a substantial fraction of expected wildfire costs when choosing where to build new homes, and how to design and maintain them. We also find that beyond relatively low levels of housing development, the marginal effect of additional homes on firefighting expenditures is surprisingly small. The failure to price fire protection essentially subsidizes low-density housing development in high-risk areas.

We use our results to construct spatially-detailed implicit subsidy measures that show that wildfire spending represents a remarkably large transfer of federal revenues to a small number of landowners in high-cost places. In our highest-risk groups, the expected NPV of the implicit subsidy is over 10 percent of total property value. We discuss three likely margins on which this subsidy may impact economic efficiency. First, noting that housing supply in the ex-urban and rural areas in which we measure the largest subsidies is likely to be highly elastic, we anticipate that the effect of this arrangement is a larger number of households in risky areas than would be observed under an alternative policy. Second, because per-household suppression expenditures decline sharply in housing density, it is likely that housing density in high-risk areas is lower under the current policy than would be observed under a policy in which homeowners paid their share of suppression expenditures. Finally, homeowners have less private incentive to make defensive investments. Our empirical analysis provides a roadmap for calculating an optimal "fire protection fee" to internalize wildland firefighting costs and mitigate these distortions.

Our results for wildfires underscore the importance of institutions in adapting to climate change. The costs of wildfires will continue to increase as the climate warms. Meanwhile, in the absence of policies that change incentives, the current pattern of new residential construction in high-risk places is likely to continue unabated. For wildfires, as for many other impacts of climate change, the ultimate costs of a warmer planet will be determined not only by the degree of physical change but also by the mediating influence of public policy.

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Figure 1: The Market for Housing in a Risky Place

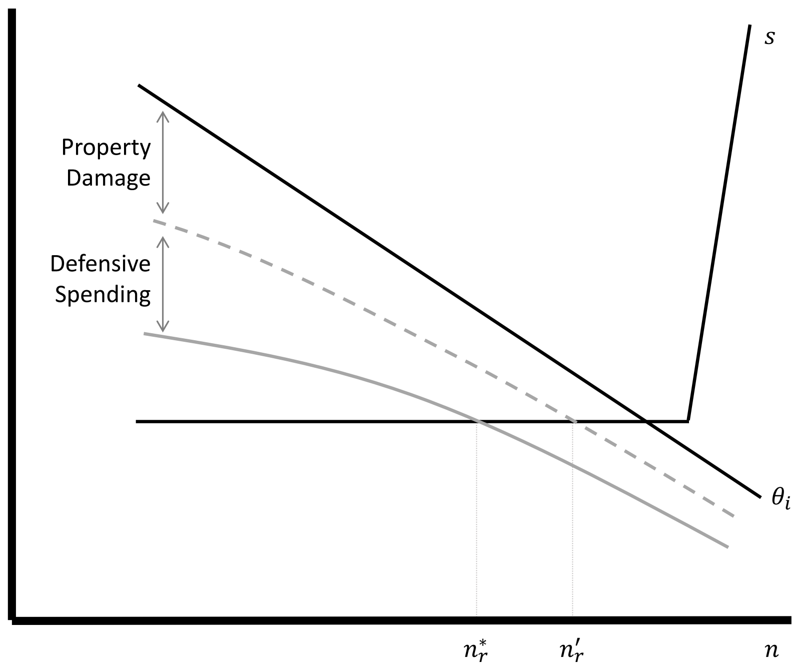
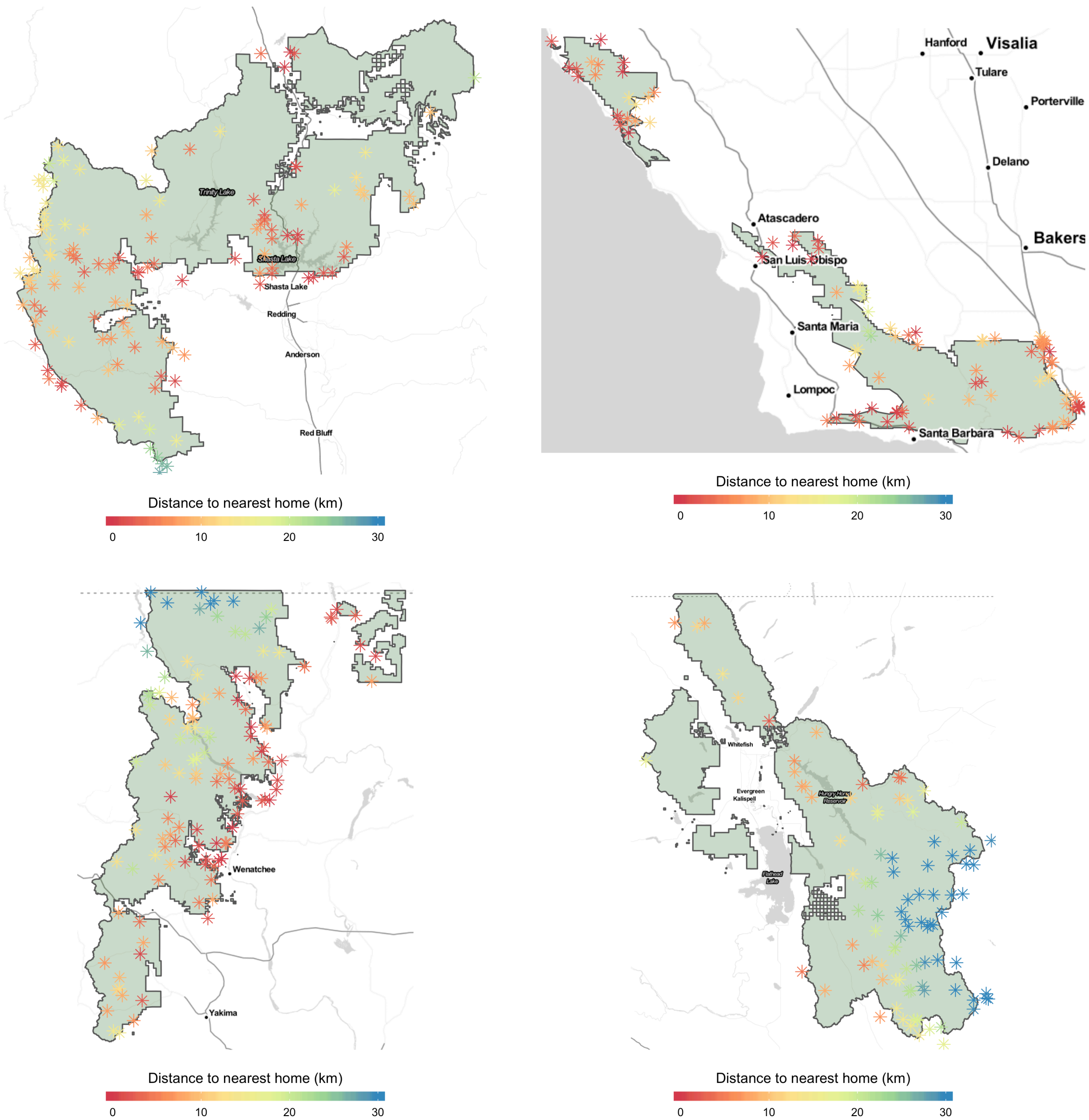
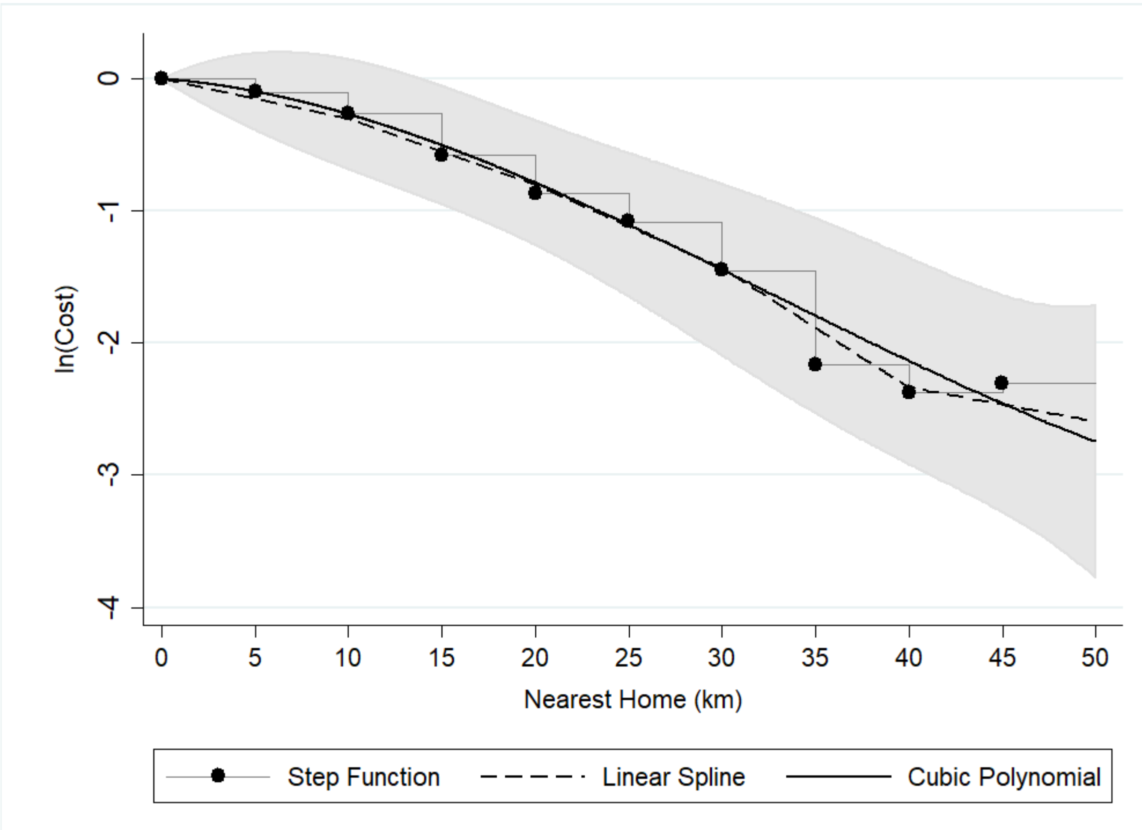


Figure 2: Example National Forest Units



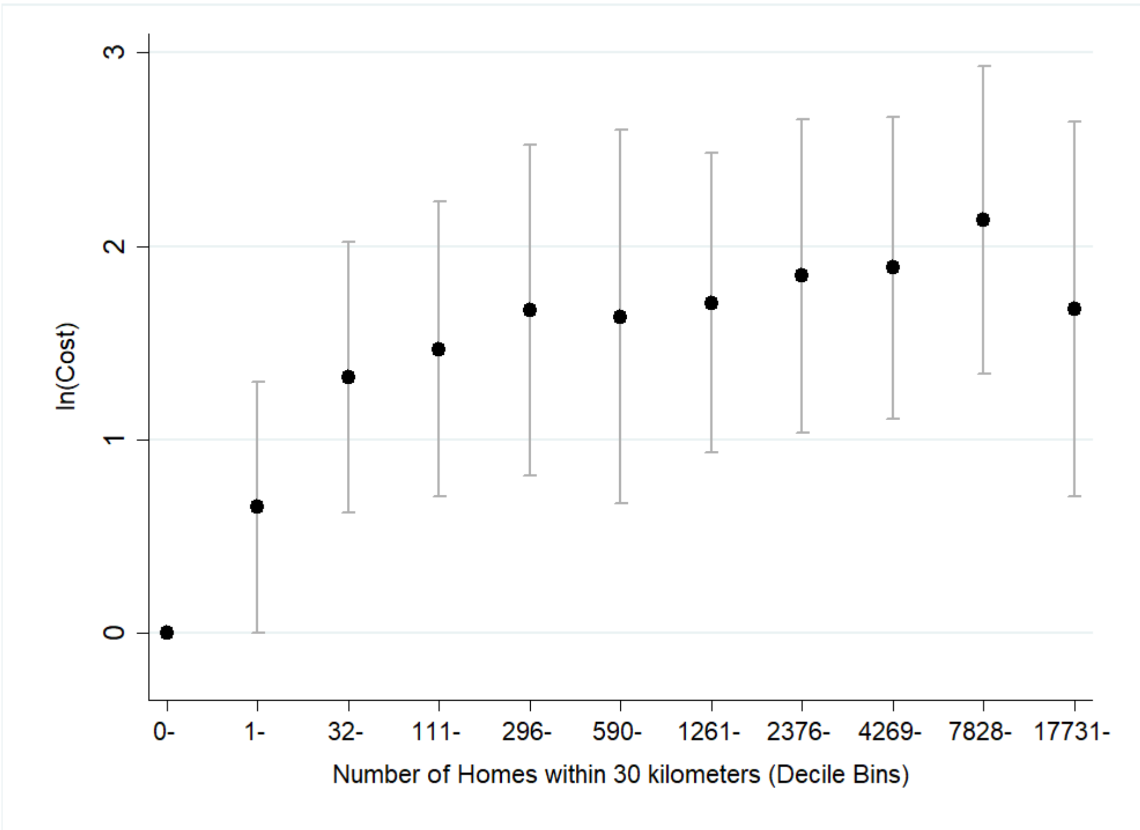
Notes: Each panel shows a single national forest area in light green. The X's represent individual wildfires, colored according to the distance to the nearest home. Clockwise from upper left, the forests are Shasta Trinity National Forest (California), Los Padres National Forest (California), Okanogan-Wenatchee National Forest (Washington), and Flathead National Forest (Montana).

Figure 3: The Effect of Homes on Firefighting Costs



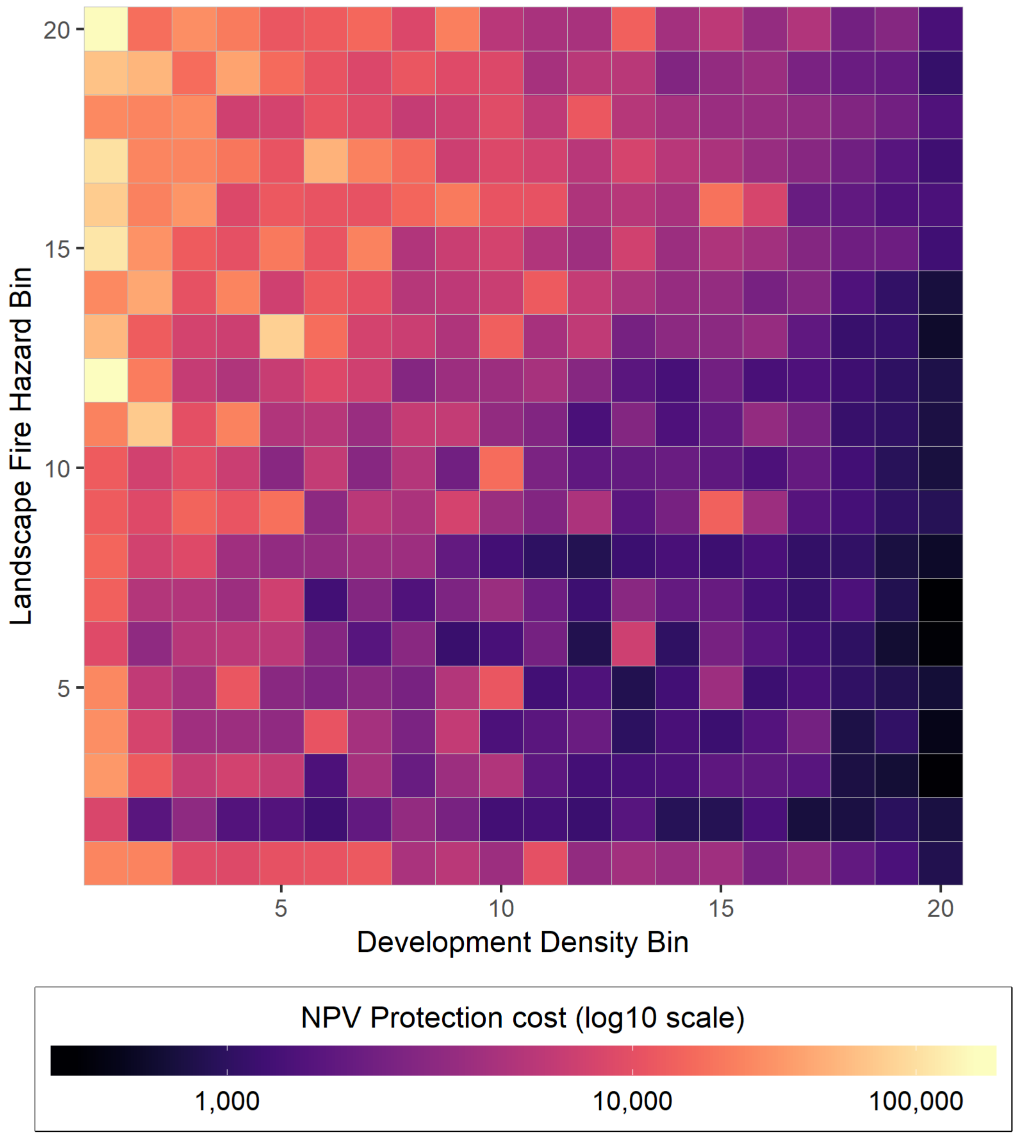
Notes: This figure reports results of three separate regressions of log firefighting cost on distance from the ignition point to the nearest home. The step function plots coefficients from a regression of log costs on indicators for 5 km distance bins. The linear spline is a piecewise linear regression with knots every 10 km. The gray shaded area around the cubic polynomial is the 95% confidence interval for that model. Each regression includes national forest fixed effects, state by month-of-year fixed effects, and state by year fixed effects. Standard errors are clustered by national forest.

Figure 4: Non-linear effects of the number of nearby homes



Notes: This figure reports results from a regression of log suppression cost on the number of homes near the ignition point. Points and error bars correspond to the point estimate and 95% confidence interval for the corresponding dummy variable in a regression of log fire suppression cost on deciles of home counts with 30 kilometers of the fire's ignition point, controlling for state by year and state by month of year fixed effects. Each regression includes national forest fixed effects, state by month-of-year fixed effects, and state by year fixed effects. Standard errors are clustered by national forest.

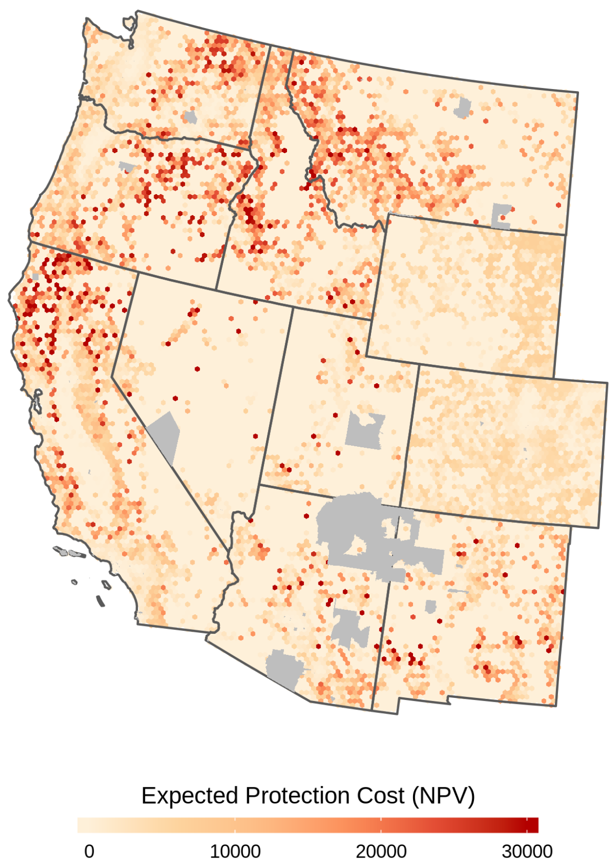
Figure 5: Average Protection Costs for 8 Million W.U.I. Homes



Notes: This figure shows the average net present value of realized historical protection costs according to fire hazard and development density. The horizontal axis shows 20 quantile bins defined by the grid cell-level distribution of population density in the study area. The 20 vertical-axis bins are defined by the wildfire hazard potential score (Dillon 2015). A single bin includes homes in areas with zero WHP, and the remaining 19 bins follow the distribution of non-zero WHP scores. Reported costs are NPV estimates based on the "suppression plus" cost metric and a 5% discount rate.

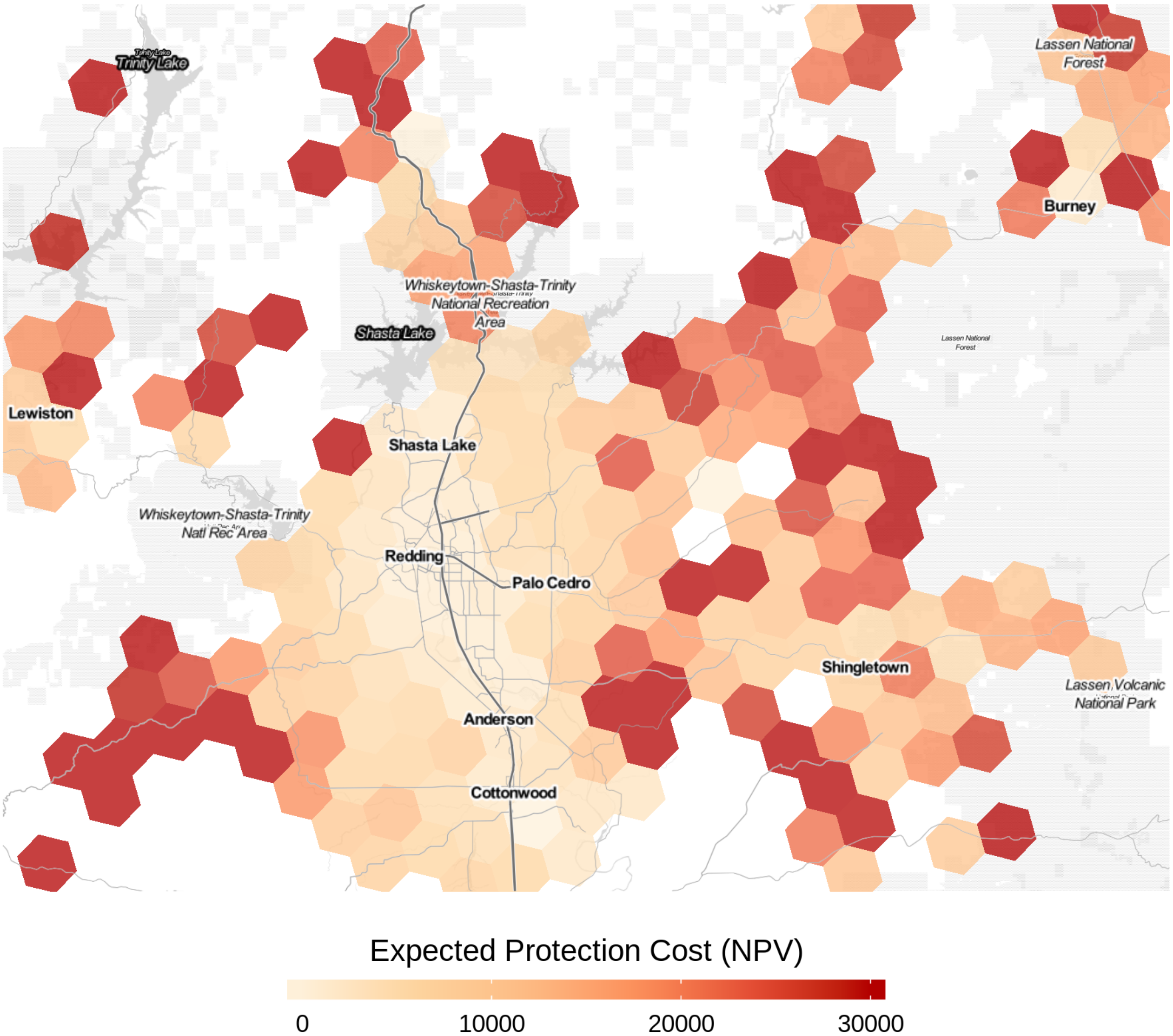
Figure 6: Expected Protection Cost by Region

"Suppression Plus" Cost Measure



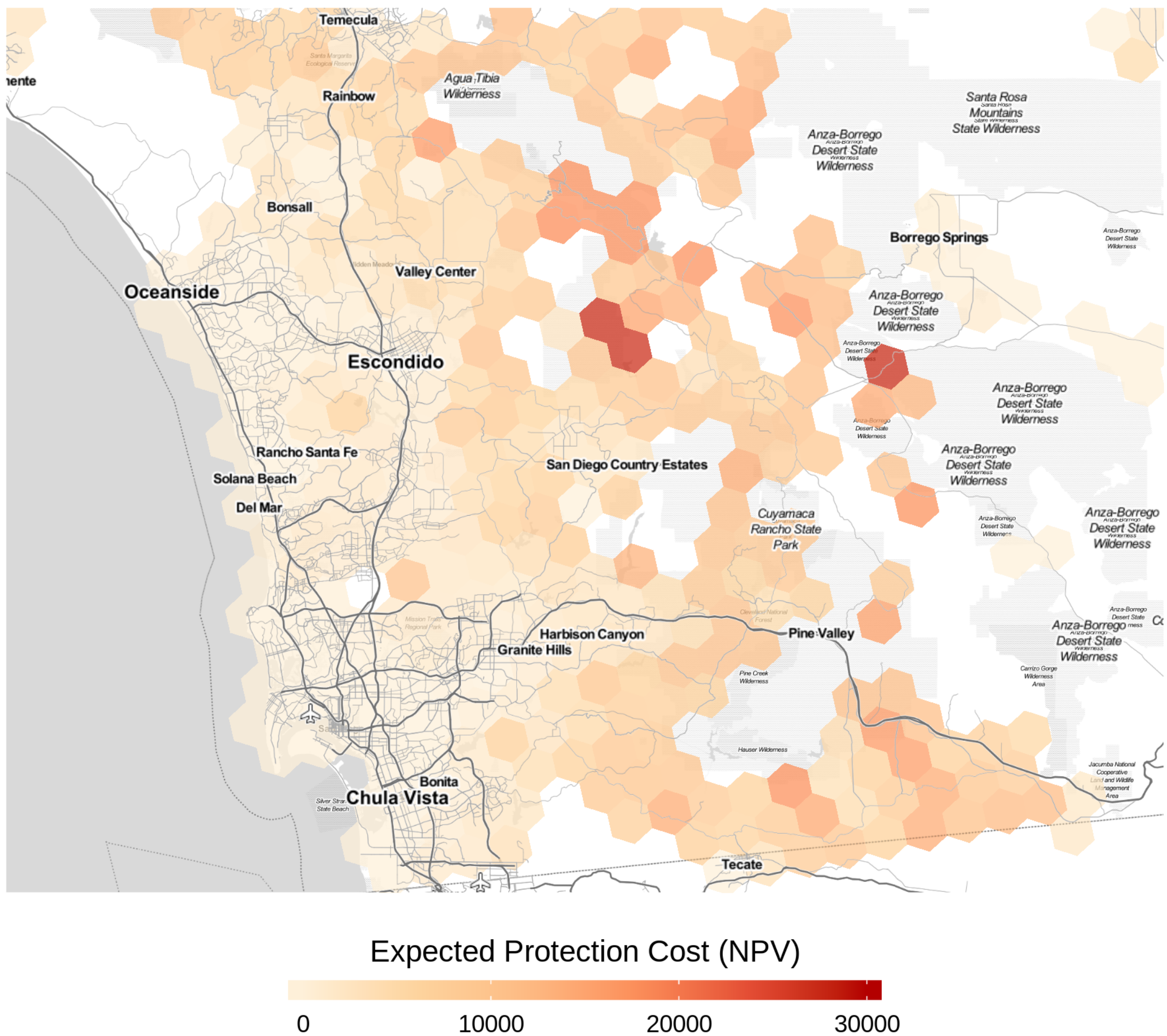
Notes: This figure shows the net present value of the additional future costs incurred by the federal government to protect a home from wildfires, averaged across 15 km hex cells. The sample includes 8 million homes near wildland vegetation areas. Map includes USFS and DOI direct suppression expenditures and preparedness costs, along with FEMA reimbursements to state firefighting agencies. See Section 6 for a detailed description of the construction of these measures. Units for the color scale are dollars per home. Gray areas indicate missing data (for example, Indian reservations).

Figure 7A: Local variation in Expected Cost



Notes: This map shows expected protection costs averaged by 5 km hex cells for Shasta County in Northern California. The color scale indicates the average expected NPV of a home's protection cost, and is top-coded at $30,000. White and crosshatched areas are unpopulated areas and public lands.

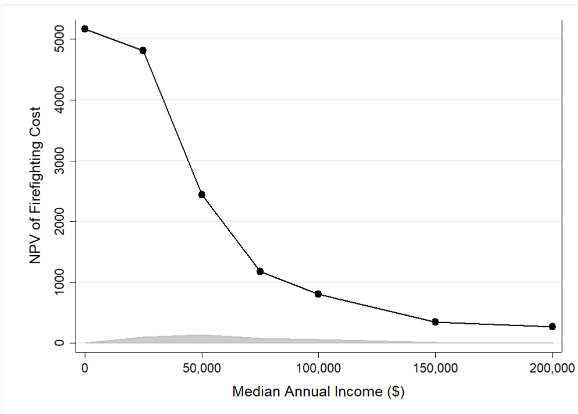
Figure 7B: Local variation in Expected Cost, Continued



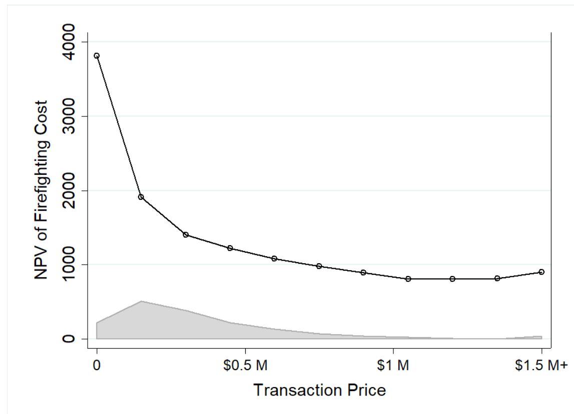
Notes: This map shows expected protection costs averaged by 5 km hex cells for San Diego County in Northern California. The color scale indicates the average expected NPV of a home's protection cost, and is top-coded at $30,000. White and crosshatched areas are unpopulated areas and public lands

Figure 8: Expected Parcel Protection Cost According to Income and Wealth

(a) Income



(b) Transaction Value



Notes: Each panel shows the variation in the net present value of expected protection costs along a single margin of interest. The black line in each panel shows average expected protection costs. The gray density shows the distribution of homes. Panel (a): Each home is assigned the median annual income for its Census block group from the 2015 American Community Survey. Panel (b): This calculation uses the subset of homes with non-missing transaction values; see data appendix for details.

Table 1: The Effect of Proximity to Homes on Firefighting Costs

	(1)	(2)	(3)	(4)	(5)
Distance to Homes (km)					
10–20	-0.34**	-0.34**	-0.42**	-0.37*	-0.46
	(0.15)	(0.15)	(0.19)	(0.21)	(0.32)
20–30	-0.98***	-0.92***	-1.01***	-0.99***	-1.52***
	(0.28)	(0.27)	(0.37)	(0.35)	(0.57)
30–40	-1.74***	-1.67***	-1.68***	-1.72***	-2.50***
	(0.46)	(0.45)	(0.51)	(0.50)	(0.73)
40+	-2.08***	-2.02***	-1.94***	-2.12***	-2.21**
	(0.41)	(0.38)	(0.46)	(0.45)	(0.91)
Controls for Weather, Topography, and Vegetation		X	X	X	X
National Forest FE	X	X	X	X	X
Year by State FE	X	X		X	X
Month-of-Year by State FE	X	X		X	X
Month-of-Sample by State FE			X		
Lightning fires only				X	
Timber Fuels only					X
Fires	2,069	2,069	2,069	1,462	768
R^2	0.41	0.42	0.53	0.45	0.58

Notes: This table reports the results of five separate OLS regressions. The sample includes western U.S. fires managed by the Forest Service during 1995-2014. In each regression the dependent variable is the natural log of suppression cost. The table rows report coefficients and standard errors on dummy variables corresponding to distance to the nearest home. The omitted category is 0–10 kilometers. Controls for weather, topography, and vegetation include wind speed, wind speed squared, terrain slope, slope squared, vapor pressure differential (VPD), VPD squared, precipitation, precipitation squared, an indicator for south/southwest facing, and indicators for fuel models (vegetation types) from LANDFIRE. Weather variables are measured on the day of ignition and topographic variables are measured at the ignition site. See online appendix for regression coefficients for these controls. National forest fixed effects include the 88 national forests in the western U.S. Standard errors are clustered at the national forest level.

Table 2: Expected Parcel Protection Costs for 8 Million Western Homes

	(1) **Federal Suppression Only ($)**	(2) **Suppression Plus ($)**	(3) **California Only ($)**	(4) **Share of Property Value (%)**
Mean	1,134	2,488	3,182	1.4
p50	700	1,500	2,000	0.7
p90	2,400	4,800	7,100	2.9
p95	3,500	7,700	8,800	5.1
p99	11,500	22,000	18,600	18.1
N	8,101,994	8,101,994	3,169,087	8,101,994.0

Notes: This table describes the distribution of expected firefighting costs for homes in the western United States. These costs represent the additional costs incurred by the federal government to protect each home, and are calculated using 210 actuarial groups based on six categories of landscape fire risk, five categories of housing density, and seven wildland firefighting dispatch regions (GACC regions). Costs are present values using a 5% discount rate. The first three columns report expected costs using three different metrics defined in the text. The final column reports the "suppression plus" cost measure divided by the transaction value of the property. Values are in 2014 dollars. See text for details.

A Additional Results and Robustness Checks

A.1 Effect of Homes on Fire Costs: Robustness checks

Appendix Table 1 shows the results from Table 1 in the main text, including coefficients on the control variables as well as an additional "no controls" specification.

Appendix Table 2 shows additional robustness checks for the effects of the number of nearby homes on fire costs. Columns (1) through (5) show the same checks that we show in Table 1 for the effect of the nearest home on fire costs. Our results are robust to these various tests. The estimated effects of the other fire characteristics are also very similar to those in Table 1, as expected. Column (6) shows an additional specification that measures the stock of nearby homes by total transaction value, instead of number of homes. Results are similar.

Appendix Figure 1 shows the effects of the number of nearby homes on fire costs using alternative radii around the ignition point to count the number of homes. Each set of markers ten equal-observation bins corresponding to the distribution of number of homes, conditional on any homes within the radius. The omitted category in each regression is fires with zero homes within the radius. For all three radii, there is a clear pattern of quick increases across the first two bins, and then roughly constant costs at higher numbers of homes. Note that direct comparisons of these coefficients across bins are difficult, since the comparison group of fires with zero threatened homes is systematically different across columns (e.g., for 40 km, all fires with zero homes are very remote by construction). Several other effects also presumably occur simultaneously as we widen the radius: since further-away homes have less effect on costs, these measures attenuate somewhat; however, because calculating density over a wider area reduces noise in our assessment of the number of threatened homes, there is another factor making these measurements more precise. Finally, note that the actual bin endpoints vary across models. The choice of radius is ultimately a somewhat arbitrary decision. Importantly, however, the obvious non-linear pattern of costs by number of homes exists for any radius.

Appendix Table 1: The Effect of Proximity to Homes: Full Results

	(1)	(2)
10–20 km	-0.5236***	-0.3394**
	(0.1683)	(0.1484)
20–30 km	-1.1381***	-0.9174***
	(0.3278)	(0.2702)
30–40 km	-2.5086***	-1.6710***
	(0.3750)	(0.4508)
40+ km	-2.7259***	-2.0173***
	(0.3799)	(0.3816)
WindSpeed		0.0644*
		(0.0345)
WindSpeed^2		-0.0017
		(0.0013)
TerrainSlope		0.0414**
		(0.0180)
TerrainSlope^2		-0.0007*
		(0.0004)
VaporPressureDifferential		0.0680*
		(0.0369)
$\text{VaporPressureDifferential}^2$		-0.0015**
		(0.0007)
Precipitation		-0.0511
		(0.0438)
Precipitation^2		0.0010
		(0.0010)
South/SW Aspect		0.2357*
		(0.1348)
Shrub Fuel Model		-0.1258
		(0.1920)
Timber Fuel Model		-0.0826
		(0.1537)
Urban/Barren Fuel Model		-0.1856
		(0.2449)
Constant	13.5350***	10.8206***
	(0.1856)	(1.6206)
National Forest FE		X
Year by State FE		X
Month-of-Year by State FE		X
Fires	2,069	2,069
R^2	0.09	0.42

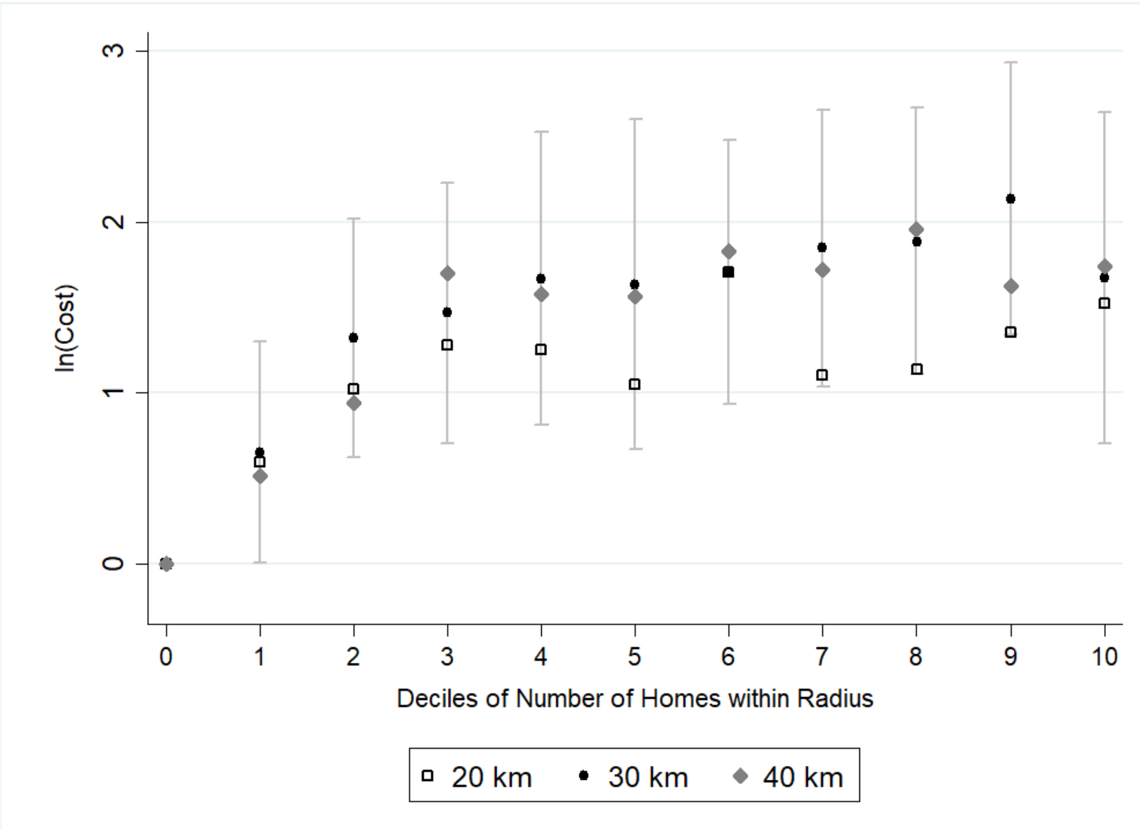
Notes: Column (2) reproduces Column (2) of Table 1, showing coefficients for the controls. Column (1) shows a no-controls specification for comparison. Terrain slope is the linear slope of the ground surface. Wind speed is average speed on the day of ignition at the reference weather station listed in FAMWEB (in miles per hour). Vapor pressure deficit is for the ignition location and day, from PRISM, and measured in hectopascals (millibars). Precipitation is the amount of precipitation on the ignition day in mm, from PRISM. Fuel model fixed effects include four categories corresponding to LANDFIRE fuel models for brush, grass, timber, and barren/urban/other. The omitted fuel model category is grass. Forest unit fixed effects include the 88 national forests in the Western U.S. Standard errors are clustered at the national forest level.

Appendix Table 2: The Effect of Number or Value of Homes, Robustness Checks

	Number					Value
	(1)	(2)	(3)	(4)	(5)	(6)
Quintile Bins						
1	0.97***	0.94***	0.90**	1.00***	1.14	0.91***
	(0.31)	(0.31)	(0.35)	(0.34)	(0.69)	(0.32)
2	1.53***	1.46***	1.38***	1.46***	1.41**	1.44***
	(0.38)	(0.37)	(0.40)	(0.39)	(0.54)	(0.39)
3	1.61***	1.57***	1.38***	1.43***	1.91***	1.69***
	(0.46)	(0.43)	(0.48)	(0.46)	(0.66)	(0.39)
4	1.85***	1.77***	1.75***	1.74***	2.30***	1.64***
	(0.38)	(0.36)	(0.44)	(0.42)	(0.64)	(0.36)
5	1.89***	1.82***	1.55***	1.77***	1.98***	1.95***
	(0.44)	(0.41)	(0.47)	(0.50)	(0.73)	(0.39)
Controls for Weather, Topography, and Vegetation		X	X	X	X	X
National Forest FE	X	X	X	X	X	X
Month-of-Year by State FE	X	X		X	X	X
Year by State FE	X	X		X	X	X
Month-of-Sample by State FE			X			
Lightning fires only				X		
Timber Fuels only					X	
N	2,069	2,069	2,069	1,462	768	2,069
R^2	0.41	0.42	0.53	0.44	0.57	0.42

Notes: Columns (1) through (5) reproduces estimates form Figure 4 in the main text, using bins of the number of homes within 30 kilometers as the variables of interest. The bins are equal observation bins for fires with at least 1 nearby home (see Figure 4 for bin ranges). The omitted category is fires with zero nearby homes. Column (6) shows an alternative specification that measures the stock of homes within 30 km by total transaction value. Again, bins are equal observation bins for fires with at least 1 nearby home, and the excluded category is fires with zero nearby homes. See Table 1 for details on controls for weather, topography, and vegetation. Standard errors are clustered by national forest.

Appendix Figure 1: Costs by Number of Homes: Alternative Radii



Notes: This figure reproduces Figure 4 from the main text using alternative radii. Each set of markers shows coefficients from a single regression using a different radius around the ignition point of the fire. The bins correspond to deciles of the distribution of number of homes within the radius, conditional on any homes within the radius. The omitted category in each regression is fires with zero homes within the radius. For all four radii, there is a clear pattern of quick increases across the first three to four bins, and then roughly constant costs at higher numbers of homes. Note that direct comparisons of these coefficients across specifications with different radii are difficult, since the comparison group of fires with zero threatened homes is systematically different across columns (e.g., using the 40 km radius, all fires with zero homes are very remote by construction). The choice of radius is ultimately a somewhat arbitrary decision. Importantly, however, the obvious non-linear pattern of costs by number of homes exists for any radius.

A.2 Effect of Homes on the Number of Fires

To evaluate whether the addition of new homes causes a larger number of fires (in addition to larger expenses on each fire that occurs), we take advantage of panel variation in home construction near each of the national forests in our dataset. We construct a year-by-national forest panel including 67 national forests and 20 years of fire experience. Because new homes are most likely to affect the number of ignitions in places with relatively low levels of development, we exclude national forests that had more than 150,000 homes within 30 kilometers of the national forest boundary in 1995 (this excludes the 20% of most densely-populated national forests).

We implement a variety of panel regression specifications. Our preferred statistical approach is a Poisson regression, since the number of fires in each national forest-year is a count variable with many zeros and a small number of other values.[25] The key identification challenge in this setting is to separate the effect of new home construction from other time-varying determinants of fire probability. Because homes are durable, the number of homes near each national forest increases monotonically across the sample. We adopt a variety of time trends and year fixed effects specifications to control as flexibly as possible for potential secular trends in the number of forests in each national forest caused by factors like climate change or annual drought cycles. Our results in this section should be interpreted with caution, since they rest on the somewhat strong assumption that, conditional on these controls, the trend in new home construction near each national forest is uncorrelated with other trends in fire occurrence.

Appendix Table 3 shows the results. All of these regressions include national forest fixed effects which remove the effect of time-invariant determinants of fire risk, such as local topography. Across specifications, new home development has a small positive effect on the number of fires each year. In Column (1), the estimated coefficient in the Poisson regression is 0.028. This implies that adding 1,000 new homes increases the annual number of fires in this national forest by 2.8%.[26] The average number of fires in each national forest-year is 1.7, so this implies that an additional 1,000 homes lead to 0.05 additional fires per year. Columns (2)–(5) include alternative polynomial time trends and find similar results. Column (6) instead includes year fixed effects, which allows for arbitrary annual trends at the West-wide level. Column (7) shows the same fixed effects specification in an OLS regression, for comparison to the Poisson results.

[25]We address the limitation of classic count regression, the restriction that the mean equal the variance for the estimated effects, by using a cluster-robust variance estimator which eliminates this problem.

[26]Expected changes in counts are calculated as $exp^{\beta} - 1$, where β is the Poisson regression coefficient.

Appendix Table 3: The Effect of Homes on the Number of Fires

	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson	(5) Poisson	(6) Poisson	(7) OLS
Thousands of Homes	0.028***	0.035***	0.029***	0.037***	0.033***	0.030***	0.021*
	(0.005)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.011)
National Forest FE	X	X	X	X	X	X	X
Linear Time Trend		X					
Quadratic Time Trend			X				
Regional Linear Trends				X			
Regional Quadratic Trends					X		
Year Fixed Effects						X	X
N	1,060	1,060	1,060	1,060	1,060	1,060	1,060

Notes: Notes: This table reports the results of seven separate regressions. In each regression the dependent variable is the number of fires larger than 300 acres in each national forest-year. Columns (1)-(6) show results for several Poisson regression specifications, and Column (7) shows an OLS specification for comparison. The variable of interest is the number homes within 30 kilometers of the national forest boundary, in thousands. The table reports regression coefficients and standard errors, which are calculated using a cluster robust variance estimator at the national forest level. For the Poisson specifications, the coefficients can be converted to expected percentage changes in the number of large fires using calculation $e^{\beta} - 1$. See text for details. The mean number of fires in each national forest-year is 1.7. "Regional Linear Trends" and "Regional Quadratic Trends" indicate that the regression includes separate polynomial time trends for each of the five forest service regions included in the sample area.

A.3 Considering sample selection issues

The analysis of the effect of homes on firefighting costs in Section 5 is limited to incidents larger than 300 acres.[27] This size threshold potentially introduces concerns about sample selection. If the subset of fires that escape initial attack and grow large differs with distance from homes in a way that is correlated with suppression costs, our analysis could be affected.

We address this potential issue in several ways. Perhaps most importantly, we are able to control directly for the potential confounders. Wind, weather conditions, and topography are extremely important in determining suppression difficulty and cost (Gebert, Calkin, and Yoder 2007). Table 1 and Appendix Table 1 show that controlling flexibly for these variables improves the model fit while introducing only small changes in the coefficients. This is a reassuring signal about the robustness of the results to sample selection or other omitted variables problems.

As an additional robustness check, this section presents a Heckman-style correction for sample selection (Heckman 1979). We use data on 77,749 ignitions handled by the USFS from 1995–2014. As our excluded instrument affecting a fire's likelihood of exceeding 300 acres, we propose the number of contemporaneous large fires in other areas of the same state. As we show in a related project (currently in progress), the supply of firefighting resources at peak times is highly inelastic. As a result, the number of competing large fires can affect the initial response to new fires.[28]

Table 4 shows the first-stage selection equation. The dependent variable is an indicator variable equal to one for fires that exceed 300 acres. Competing Fires is the number of fires in the same state but not the same national forest that started during the previous 10 days, exceed 300 acres, and have ignition points 25 km or less from homes. Across specifications, the number of competing fires is a significant predictor of reaching 300 acres. As expected, distance from homes is also predictive: fires that start far from homes are more likely to exceed 300 acres. This may reflect more intense initial attack efforts near homes. It may also reflect landscape factors that increase initial attack success in more developed areas, such as greater accessibility and less dense vegetation. Wind, vapor pressure differential, terrain slope, temperature, and precipitation all affect fire growth in the expected way.

Table 5 shows the main estimates corrected for selection using the two-step estimator in Heckman (1979). Column (1) shows an OLS regression of log firefighting costs on

[27] For smaller incidents, response costs are not consistently reported. They are generally charged to a single accounting code within a given national forest unit and year (these smaller incidents are sometimes referred to as "ABCD" fires).

[28] The exclusion restriction requires that this instrument does not affect suppression costs. If area burned is itself an important predictor of eventual suppression costs, this will fail to hold. On the other hand, if suppression costs are instead driven by threats to private property and weather and topographic variables, this instrument will be valid.

distance from homes and other controls. Columns (2) – (4) show corrected estimates. The corrected estimates are quite similar to the uncorrected estimates, suggesting that sample selection does not have an important effect on our estimates. The implied correlation between the first- and second-stage error terms (i.e., factors affecting selection into the sample, and factors affecting firefighting costs) is relatively small and we cannot reject the null hypothesis of no correlation. This is consistent with our results in the main text, which imply that the factors that determine whether fires reach the minimum size to be included in the cost dataset are not importantly related to factors that determine firefighting cost in a way that would affect our estimates.

Appendix Table 4: Probability of Exceeding 300 Acres

	(1) Probit	(2) Probit	(3) Probit	(4) OLS
Competing Fires	0.0019***	0.0015***	0.0012***	0.0020***
	(0.0003)	(0.0002)	(0.0002)	(0.0004)
Nearest Home (km)	0.0008***	0.0008***	0.0008***	0.0012***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Wind (mph)		0.0016***	0.0013***	0.0013***
		(0.0002)	(0.0002)	(0.0002)
Vapor Pressure Differential		0.0014***	0.0015***	0.0013***
		(0.0001)	(0.0001)	(0.0002)
Terrain Slope		0.0005***	0.0004***	0.0004***
		(0.0001)	(0.0001)	(0.0001)
Precipitation		-0.0027***	-0.0024***	-0.0015***
		(0.0005)	(0.0005)	(0.0003)
South/southwest-facing		0.0016	0.0018	0.0015
		(0.0012)	(0.0012)	(0.0013)
Fuel Model Dummies		X	X	X
National Forest Dummies			X	X
Year Dummies			X	X
N	77,749	77,749	77,494	77,749

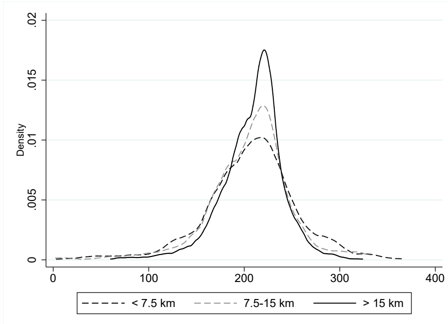
Notes: Each column reports average marginal effects from a separate regression. The dataset includes 77,749 ignitions during 1995–2014. The dependent variable is an indicator variable equal to one for fires that exceed 300 acres. "Competing Fires" is the number of fires in other national forests in the same state ignited during the previous 9 days, exceeding 300 acres in size, and located within 25 km of homes. Each regressions includes quadratic functions of Wind, VPD, slope, temperature, and precipitation. See main text for information on other variables. Standard errors are clustered at the national forest level.

Appendix Table 5: Effect of distance to homes, corrected for sample selection

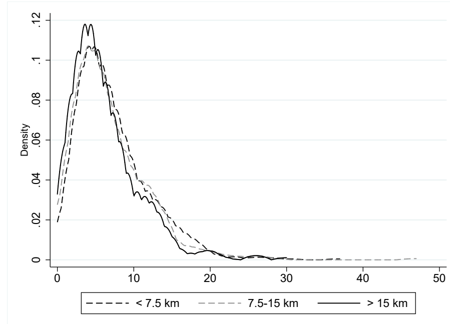
	(1) Uncorrected OLS	(2) Corrected	(3) Corrected	(4) Corrected
Distance to Homes (km)				
10–20	-0.19	-0.17	-0.27*	-0.20
	(0.16)	(0.16)	(0.16)	(0.17)
20–30	-1.19***	-1.14***	-1.02***	-0.86***
	(0.20)	(0.22)	(0.24)	(0.28)
30–40	-2.39***	-2.27***	-1.86***	-1.61***
	(0.23)	(0.32)	(0.32)	(0.39)
40+	-2.72***	-2.55***	-2.22***	-1.90***
	(0.28)	(0.43)	(0.40)	(0.50)
Wind (mph)	0.072**	0.078**	0.094***	0.111***
	(0.030)	(0.032)	(0.033)	(0.035)
Wind Squared	-0.002**	-0.002**	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Vapor Pressure Differential	0.107**	0.116**	0.134***	0.131***
	(0.046)	(0.048)	(0.045)	(0.046)
VPD Squared	-0.00*	-0.00*	-0.00**	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Terrain Slope	0.06***	0.06***	0.06***	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)
Slope Squared	-0.00*	-0.00*	-0.00**	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
Precipitation	-0.24**	-0.25**	-0.19*	-0.22**
	(0.11)	(0.12)	(0.11)	(0.11)
Precip. Squared	0.02*	0.02*	0.02*	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
South/southwest-facing	0.13	0.13	0.09	0.11
	(0.15)	(0.15)	(0.14)	(0.14)
Constant	11.10***	10.25***	10.54***	7.54***
	(0.57)	(1.69)	(1.62)	(2.40)
Fuel Model Dummies	X	X	X	X
National Forest Dummies			X	X
Year Dummies				X
N	1,491	77,484	77,484	77,484

Appendix Figure 2: Covariate Overlap by Distance from Ignition Point to Nearest Home

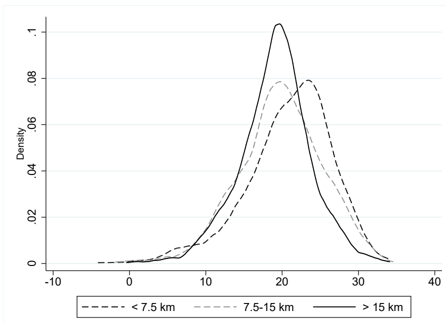
(a) Day of Year (Ignition)



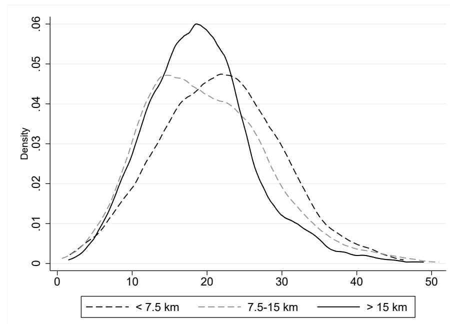
(b) Wind Speed (mph)



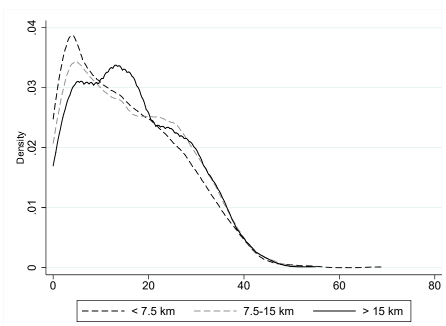
(c) Temperature (F)



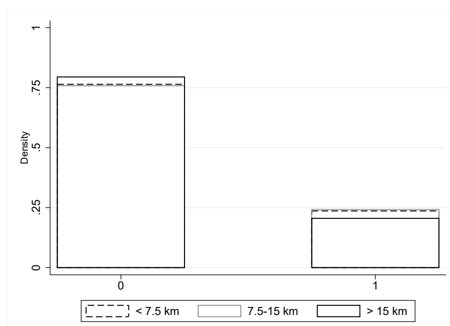
(d) Vapor Pressure Differential



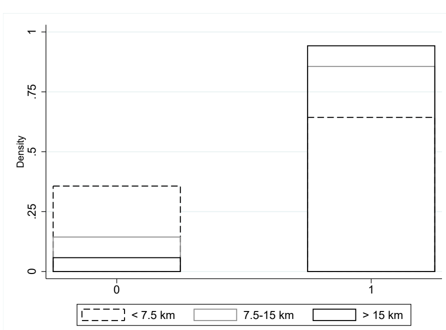
(e) Terrain Slope



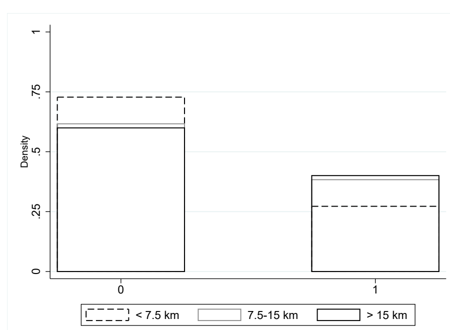
(f) South/southwest-facing



(g) Lightning-caused



(h) "Timber" fuel model



Notes: This figure shows covariate distributions for the US Forest Service fires analyzed in Table 1 and Figure 4. Panels (b), (c), and (d) report weather on the day of ignition. Wind speed is average wind speed from the reference weather station reported in FAMWEB. Temperature and vapor pressure differential are mean daily values from PRISM. Terrain slope is the slope percentage, where 100 corresponds to a slope of 1 (i.e, a 45-degree line). "Timber" fuel models follow the Anderson Fire Behavior Fuel Models.

B Construction of the dataset

Our data combine administrative data on firefighting expenditures from multiple agencies, parcel-level assessor data for the universe of western U.S. homes, topographical information, risk assessments, and weather conditions data. This section provides a complete account of the dataset construction; readers should refer to section Section 4 in the main paper for a high-level summary. Table 6 gives descriptive statistics for the dataset, Figure 2 shows how fire observables covary with distance from homes, and Figure 3 maps all of the large fires in the sample, colored by agency.

B.1 Wildland firefighting expenditures

The fire suppression and preparedness cost data cine from six different sources, including five federal agencies and one state firefighting agency. The federal agencies are the United States Forest Service, the National Park Service, the Bureau of Land Management, the Bureau of Indian Affairs, and the Federal Emergency Management Agency. The state agency is California's Department of Forestry and Fire Protection (Cal Fire). We obtained firefighting data at the incident level from each agency through a combination of Freedom of Information Act (FOIA) requests (or similar records requests for state data) and publicly available sources. Our geographical focus is the western United States. We define the "western United States" as the states of Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming. We discuss each source of data in detail below, as well as the process by which we harmonize these datasets.

B.1.1 US Forest Service

The U.S. Department of Agriculture, Forest Service (USFS) accounts for the largest share of fire suppression expenditures of any federal agency and is primarily responsible for fires that ignite in or near the boundaries of National Forest areas. We obtain historical by-incident suppression costs (primarily wage and equipment costs incurred by USFS) for fires managed by the USDA Forest Service from 1995 to 2017 from the National Fire and Aviation Management Web (FAMWEB) Database. Some institutional detail is helpful in understanding the process by which the data are compiled: the FAMWEB database represents a compilation of individual reports on fire occurrence, the conditions in which the fire ignited, and the suppression efforts undertaken by USFS. These reports are entered into the Fire Statistics System (FIRESTAT) application, which is run by the USFS. FAMWEB is the database which contains this information.[29]

Gebert, Calkin, and Yoder (2007) argue that fire suppression costs are captured more accurately by USFS accounting data than in the FAMWEB database. We therefore also obtain separate USFS accounting data on incident level expenditures through a separate Freedom of Information Act request. However, USFS was only able to provide these records for the period 2004–2012. In Appendix Section C, we conduct our empirical analysis using both the accounting data and a subset of the FAMWEB data limited to 2004–2012 and find both qualitatively and quantitatively similar results. We conclude that inaccuracies in the FAMWEB database are sufficiently limited within our sampling frame to have limited impact on our empirical questions of interest and therefore conduct the bulk of our analysis with the FAMWEB data because of its greater temporal coverage.[30]

Over the course of our sampling frame, more than 150,000 wildfire incidents are logged in this database. However, since the Forest Service only reports per-fire cost data for fires above 300 acres, we limit this sample to the 3,571 fires in the 11 western states with a size of 300 acres or larger (the smallest size for which suppression expenditures are separately reported) with ignition date and location data available.

Most ignitions are quickly suppressed at low marginal cost by "initial attack" efforts. These incidents are not included in our dataset of large fires. We address this in Section 6 by incorporating data on preparedness expenditures for USFS and the DOI agencies: these are expenditures that occur not in direct response to any particular large wildfire, but instead are undertaken to prevent or mitigate future fire risk. To identify these costs, we obtain budget justification reports from the US Forest Service website for the years 2007-2017. From these documents we extract the region-specific spending allocated towards "Fire Preparedness." In total we obtain more than 6.8 billion dollars of preparedness spending for our sampling frame.[31] These preparedness

[29] Previously, these data were compiled using Kansas City Fire Access Software, or KCFAST. Both KFCAST and FAMWEB include data on suppression expenditures and fire locations, but FAMWEB is the more current and complete of the two, with one exception: FAMWEB does not include any data on which agency was responsible for a given ignition or on the wind speed and direction at the nearest weather station at time of ignition. To obtain these additional fields, we also load and merge in the KCFAST dataset.

[30] A more subtle difference between this study and Gebert, Calkin, and Yoder (2007) is that the latter authors use the fire cost per acre as the outcome variable when considering the drivers of wildfire suppression costs, arguing that "fire managers are accustomed to thinking in terms of cost per acre," and also include the natural log of total acres burned as an explanatory variable. We choose to use total cost as the outcome variable in our regression analysis of incident costs. We also do not include a measure of acres burned as an explanatory variable. We prefer this specification for two reasons: the policy-relevant figure is the total cost of suppression; and acreage burned as the denominator and size of fire as an explanatory variable induces a reverse causality problem (since acreage is a function of suppression effort) and a "bad controls" problem (Angrist and Pischke 2009).

[31] The Forest Service regions corresponding to our sampling frame are 01, 02, 03, 04, 05, 06, 08, 09, and 10.

costs represent the cost of maintaining initial attack readiness and other fixed costs of the wildland firefighting system. Section 6 describes how we allocate these costs over ignitions.

B.1.2 Department of Interior Agencies

Four separate agencies within the Department of Interior (DOI) engage in significant fire management. They are the Bureau of Land Management (BLM), the Bureau of Indian Affairs (BIA), the National Park Service (NPS), and the U.S. Fish and Wildlife Service (FWS). We successfully obtained firefighting cost data for BLM, BIA, and NPS through FOIA requests[32]. BLM is responsible for fires that ignite on the 248 million acres of public lands they manage. BIA is responsible for fires starting on the 55 million acres of Indian trust lands, and NPS is responsible for fires igniting within its 417 park units across 84 million acres of land. Each agency provided incident-level data from 2003-2016 from its own accounting databases for fires larger than 100–300 acres. To match the data available from the Forest Service, we limit this sample to include only fires that affect more than 300 acres and apply similar data quality restrictions as those described for the USFS data. Our final DOI suppression dataset includes 3,003 BLM fires, 418 BIA fires, and 240 NPS fires.

As with USFS, we also include DOI preparedness costs in some scenarios in Section 6. The DOI agencies collectively prepare one annual budget justification that covers wildland fire activities across the entire United States. Our data on DOI preparedness costs come from the fiscal year 2012–2018 versions of these documents. In total, we account for 2.7 billion dollars of preparedness spending. Because DOI does not provide region-specific figures for these preparedness costs, we allocate them according to the proportion of total U.S. ignitions that occur within our sampling frame on an annual basis. On average, we allocate 54% of this preparedness spending to our study area to obtain a total of 1.5 billion dollars from the DOI agencies.

B.1.3 California Department of Forestry and Fire Protection

We also collect fire suppression cost data for California, which includes over 50% of the population in our sample area and some of the most frequent and costly wildfires. Suppression cost data for California come from a public records request to the California Department of Forestry and Fire Protection (Cal Fire). Cal Fire is responsible for managing wildfires on 31 million acres of State Responsibility Area lands, loosely corresponding to private- and state-owned lands outside of incorporated towns and

[32] At the time of this writing, we have not obtained firefighting suppression costs for FWS. Using the Federal Fire Occurrence Database, we find that FWS reports fewer fires and fire acres than either USFS or BLM, but more than BIA and NPS.

cities. We merge three sets of administrative records from Cal Fire. The first is a complete listing of all reported wildland fire incidents in the Cal Fire protection area during 2007–2016, regardless of size. This dataset includes the ignition date, acres burned, Cal Fire geographic unit, and, for incidents after mid-2011, the latitude and longitude of the ignition point.[33] The third dataset is an administrative record of firefighting expenditures at the incident level for 788 incidents during 2011–2016. According to CAL FIRE, these expenditure data are carefully tracked because they are the basis of cross-agency reimbursements for mutual aid expenditures – for example, reimbursements to California by the federal government under the FEMA Fire Management Assistance Grant (FMAG) program, or by local governments to CAL FIRE for firefighting assistance in incorporated areas.

Beginning with the list of significant fires, we drop incidents outside of CAL FIRE jurisdiction since these costs are ultimately borne by other agencies, such as the USDA Forest Service or municipalities. Limiting our sample to fires for which we are able to obtain precise location and suppression cost data results in 198 large fires (and 455 fires of any size) from 2011–2016.

B.1.4 Federal Emergency Management Agency

Our final agency source is the Federal Emergency Management Agency (FEMA). FEMA does not directly engage in firefighting efforts. Instead, FEMA reimburses state agencies and local governments for their costs on large firefighting efforts through the Fire Management Assistance Grant (FMAG) program. These grants reimburse 75% of the firefighting expenses incurred by state and local governments during qualifying incidents. We obtained incident-level data on FEMA reimbursements for wildfire incidents during 2000–2017 through a Freedom of Information Act request. These records contain the incident name, date, state, and amount reimbursed. They do not contain geographic coordinates (or a common identifier that would allow us to merge them to other agency data to recover geographic information). For cost scenarios in Section 6 that include FEMA reimbursements, we allocate these costs, multiplied by 1.33 to include the non-reimbursed portion, over fires in each year-state cell similarly to preparedness costs. In any calculation where we include Cal Fire cost data, we do not include FEMA reimbursements to California, which presumably include costs incurred by Cal Fire.

[33] To supplement the location records for earlier fires, we also obtain shapefile data for a subset of CalFire incidents from the publicly available Fire and Resource Assessment Program database managed by Cal Fire.

B.1.5 Fire expenditures harmonization

To ensure consistent data quality, we harmonize the data across all agencies from which we source suppression expenditures. Specifically, we ensure that ignition date, ignition location, responsible agency, cause of fire, area burned, and suppression cost data are present for all incidents and that the costs reflect values in 2014 dollars. Federal, state, and local firefighting agencies provide assistance to one another through coordinated dispatch systems and mutual aid agreements. We carefully considered the implications of this aid for our analysis. We confirmed with each agency that its reported costs represent only that agency's costs for a given incident (except for FEMA reimbursements). Thus, we avoid double counting when adding up historical costs across agencies in Section 6. When investigating the effect of homes on costs in Section 5.1, we use only USFS cost data and further limit the sample to incidents where USFS was the primary responsible agency. This restriction is used by Gebert, Calkin, and Yoder (2007), who argue that USFS bears at least 90% of the costs of these fires.[34]

We have also attempted to ensure that cost concepts are at least broadly comparable across agencies. In general, the firefighting cost data in the final dataset include wages (salaries, overtime, hazard pay) and equipment costs. Usage costs for agency-owned equipment (as opposed to equipment from private contractors) are tracked somewhat differently by different agencies. For example, in direct correspondence BLM indicated that they assign mileage costs for regular vehicles and engine-hour costs for fire engines to each incident, while NPS indicated that they assign only fuel and repair costs. The allocation of salary costs between "preparedness" and "suppression" budget categories may also differ somewhat across agencies.

Finally, we compute the spatial relationship between each fire and potentially valuable resources nearby. Specifically, we measure the distance from the ignition point of each fire to the nearest parcel in the parcels dataset described in Section B.2, the nearest state or federal highway, and the count of homes and their value within x km of the ignition point, where $x \in \{5, 10, \ldots, 50\}$. Our final dataset includes 7,430 fires and accounts for nearly 11 billion dollars of suppression costs.

B.1.6 Ignition point characteristics and weather data

Using the harmonized location data, we obtain elevation, slope, aspect, and fuel model data for the ignition point of each fire from LANDFIRE. The former three products are derived from the high-resolution National Elevation Dataset; elevation represents

[34]Ideally, we would sum each agencies expenditures on each individual incident. Unfortunately, USFS and the DOI agencies do not reliably use consistent incident identifiers, making such a merge impossible.

Appendix Table 6: Descriptive statistics

Panel A: Pooled fire characteristics

	Mean	P10	P50	P90
Area burned	7,873	383	1,433	16,034
Fire cost	2,350,820	9,066	227,461	5,233,689
Elevation	1,554	707	1,559	2,353
Slope	12	1	10	29
Aspect	142	-1	135	306
Temperature	20	13	21	27
Precipitation	0	0	0	1
Vapor Pressure Deficit	21	11	21	32
Nearest home distance	14	1	10	33
Parcels in 5km	147	0	0	107
Parcels in 10km	709	0	0	1,027
Parcels in 20km	3,110	0	92	6,768

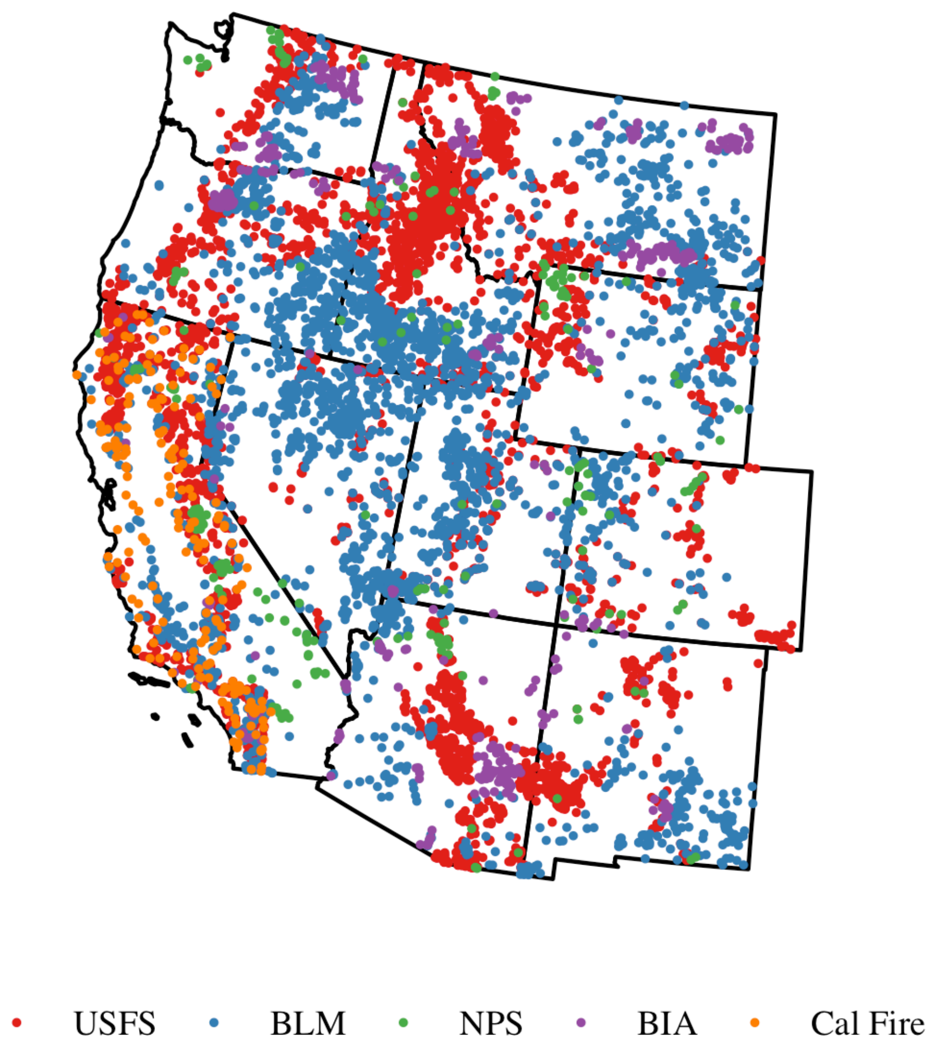
Panel B: Fire characteristics by agency

	USFS	BLM	BIA	NPS	CAL FIRE
Number of fires	2,419	1,617	315	126	104
Acres burned (1000s)	19,442	13,435	1,814	685	690
Suppression cost (m)	8,799	507	257	94	854

Notes: This table reports descriptive statistics for the 6,422 fires with area greater or equal to 300 acres in our sample. P10, P50, and P90 indicate the 10th, 50th (median), and 90th percentile of values. Aspect is given in degrees, elevation is in meters above sea level, fire cost is in 2014 US $, nearest home distance is in kilometers, parcels is the number of parcels within the given distance, precipitation is in mm, slope is in degrees, temperatures is in Celsius, and Vapor Pressure Deficit is in millibars.

the land height above sea level and is given in meters, slope represents the angle the land and is given in degrees, and aspect represents the direction of the slope and is given in degrees as well. The fuel model data are the 13 Anderson Fire Behavior Fuel Models and describe the fire potential of surface fuel components (e.g., the type of foliage in the area) on which the fire starts. We also obtain ignition-day weather (maximum and minimum temperatures, precipitation, and measure of humidity) from the PRISM daily weather dataset, as well as ignition-day wind direction and speed from the FAMWEB dataset.

Appendix Figure 3: Western Wildfires, 1995–2017



Notes: Map of fires in sample. Includes all fires between 1995 and 2017 larger than 300 acres. Color of point indicates which agency provided data.

B.2 Parcel data

The homes data include information on home locations, values, year built, and other property characteristics for 18.5 million parcels, or nearly all of the single-family homes in the western United States. We also include parcels within 50 km of these states to accurately capture the nearness and number of parcels for wildfires that occur near the eastern borders of our sample. These data are provided by CoreLogic and represent a compilation of tax assessor data from individual counties.[35] A primary advantage of these data is the inclusion of detailed locational information; specifically the data include both latitude and longitude as well as street address for each parcel. While previous studies in this area rely on publicly available data on the number and value of homes in a census block (Gebert, Calkin, and Yoder 2007; Gude, Jones, Rasker, and Greenwood 2013), this confidential dataset enables us to precisely locate homes relative to wildfire ignition points. Because census blocks can be large in rural areas and particularly when located near national forests, the standard approach using census block centroids introduces substantial noise into the estimate of distance-to-nearest parcel for each fire. In Section B.2.1 we document the improved locational precision and the data quality benefits produced by this approach.

We limit the sample to include only homes in partially vegetated areas that would be threatened by wildland fires, based on wildland-urban interface (WUI) categories identified in Radeloff et al. (2005). Specifically, we include homes located in the following vegetation categories: high density interface, high density intermix, medium density interface, medium density intermix, low density interface, low density intermix, very low density vegetated, and uninhabited vegetated[36]. We exclude homes in areas without wildland vegetation, and specifically in areas with the following categories: high density no vegetation, medium density no vegetation, low density no vegetation, very low density no vegetation, and uninhabited no vegetation. Because the federal government controls so much land in the West, and so much residential development is in wildland areas, these sample exclusions are not particularly restrictive. Our analysis dataset includes 8,739,351 homes (about 47% of all single-family homes in the West). We also link the parcels to the USFS Wildfire Hazard Potential (WHP) ratings to assess physical fire risk (Dillon 2015). These risk scores are designed to "depict the relative potential for wildfire that would be difficult for suppression resources to contain," and combine data from a large-scale fire simulator with spatial fuels and vegetation data to produce indicators of WHP. For each parcel, we assign a categorical and a continuous measure of WHP for that location as a measure of the risk faced by that parcel. We also add a measure of population density (population per square meter) from the Gridded Population of the World dataset, which reports

[35] We access the CoreLogic data through a data-sharing agreement with Stanford University.

[36] Because the WUI data are built from Census records and our parcel data represent precise locations, occasionally a parcel is located in a so-called "uninhabited vegetated" area. Because we rely on the WUI data to identify vegetated areas, we include homes in these areas as well

density within roughly 1km square grid cells.

B.2.1 Alternative methods for locating parcels

Our study uses parcel-level data to assess the locations of homes threatened by wildfire. Previous studies rely on counts of housing units at the Census block scale (Gebert, Calkin, and Yoder 2007; Gude, Jones, Rasker, and Greenwood 2013). Section B.2.1 demonstrates that high-risk regions are systematically likely to have large Census block sizes. The average Census block size for homes in the highest decile of firefighting cost is 5 square km, and the 95th percentile is over 20 square kilometers. This large grid size introduces substantial noise into geographic analyses of aggregate home counts. Our study instead uses parcel-level data to assess home locations. This represents a substantial increase in granularity over existing studies.[37] The degree of this advantage over aggregate block-level data depends on the accuracy with which parcel locations are reported in the real estate data. The underlying records in this dataset are collected by county tax assessors, and the quality of the data varies across counties. In the following section, we describe the process by which we obtain highly accurate parcel locations for the dataset and the advantages this provides relative to using Census block centroids.

The process of generating geographic coordinates for individual structure locations is called geocoding. This section compares the default geocoding for the homes in our dataset to an alternative geocoding algorithm. We also compare our results using methods to identify homes based on publicly available data that have been used in related work (e.g. Gebert, Calkin, and Yoder 2007; Radeloff et al. 2005; Radeloff et al. 2018).

The housing data used in this project come from CoreLogic. This dataset includes a field identifying the latitude and longitude of each home in the dataset. Overall, careful investigation of subsamples of the data imply that these coordinates are quite accurate. However, these default locations often locate multiple homes in precisely the same geographic location. To improve the accuracy of parcel locations, we implemented a secure, locally-hosted geocoding algorithm on a local server to calculate coordinates for each home. We used a locally hosted instance of the Nominatim geocoder[38] to geocode homes in our dataset based on the address field, while maintaining data confidentiality and security.

Overall, the geographic coordinates generated by Nominatim align closely with the

[37] A separate advantage of parcel-level data over Census data is that we know the year in which a home was constructed, and thus whether the home was present at the time of each fire in the dataset. Census data report static housing counts every 10 years.

[38] Nominatim uses Open Street Map data to conduct forward and reverse geocoding and is available at https://github.com/openstreetmap/Nominatim.

default locations in the homes data. The median distance between reported locations is 41 meters. For most homes, we believe that the Nominatim locations represent small shifts that slightly improve location accuracy. The exception is for addresses that include typographical errors. In this case, Nominatim may return locations that are not meaningful – for example, that may be hundreds of kilometers outside of the county containing the home.[39] To eliminate these errors, we backstop the Nominatim locations with the default locations in the original dataset (which tend to be more accurate but less precise) using the following rule: if the Nominatim location is A) more than 1km outside of the county given in the CoreLogic data, B) differs from the CoreLogic location by more than 5 km, or C) was not obtained using the street address (e.g., was geolocated by the Nominatim algorithm based only on city and state), we use the CoreLogic location instead. Using this backstop method, we recode 89% of the addresses in our full dataset using Nominatim, and the remainder with the default locations in the original dataset.

Previous studies of wildland-urban interface issues have used publicly-available Census data to identify approximate home locations. The decennial Census includes counts of population and housing units at the Census block level. Forestry studies frequently use these block-level aggregate data to locate homes (e.g., by average population over the area of the Census block, or assigning population to the centroid).[40] One challenge with using aggregate Census data is that Census blocks in areas with high fire risk tend to be many square kilometers or more, reducing the accuracy of the approach. Table 7 shows this. On the other hand, Census block-based approaches do not rely on the accuracy of address-based geocoding.

The figures and tables in this section explore the robustness of our results to three possible methods to locating homes: our geolocation method, a method that follows previous work in using Census block centroids for homes' locations, and a method using the Census-based list of places (which include both incorporated and unincorporated communities). Figure 4 shows that the results are not qualitatively sensitive to the choice of location method. However, both of the census-based approaches identify few fires with homes more than 40 km away and the corresponding standard errors for the estimate of the effect of home nearness on fire suppression cost are noisier. In our view, both of these facts reflect that the census-based approaches systematically underestimate (on average) the distance to nearest home for fires in remote areas for the reasons we describe above.

[39] The County field in the underlying dataset is likely to be particularly reliable, since the dataset is assembled from individual county tax records.

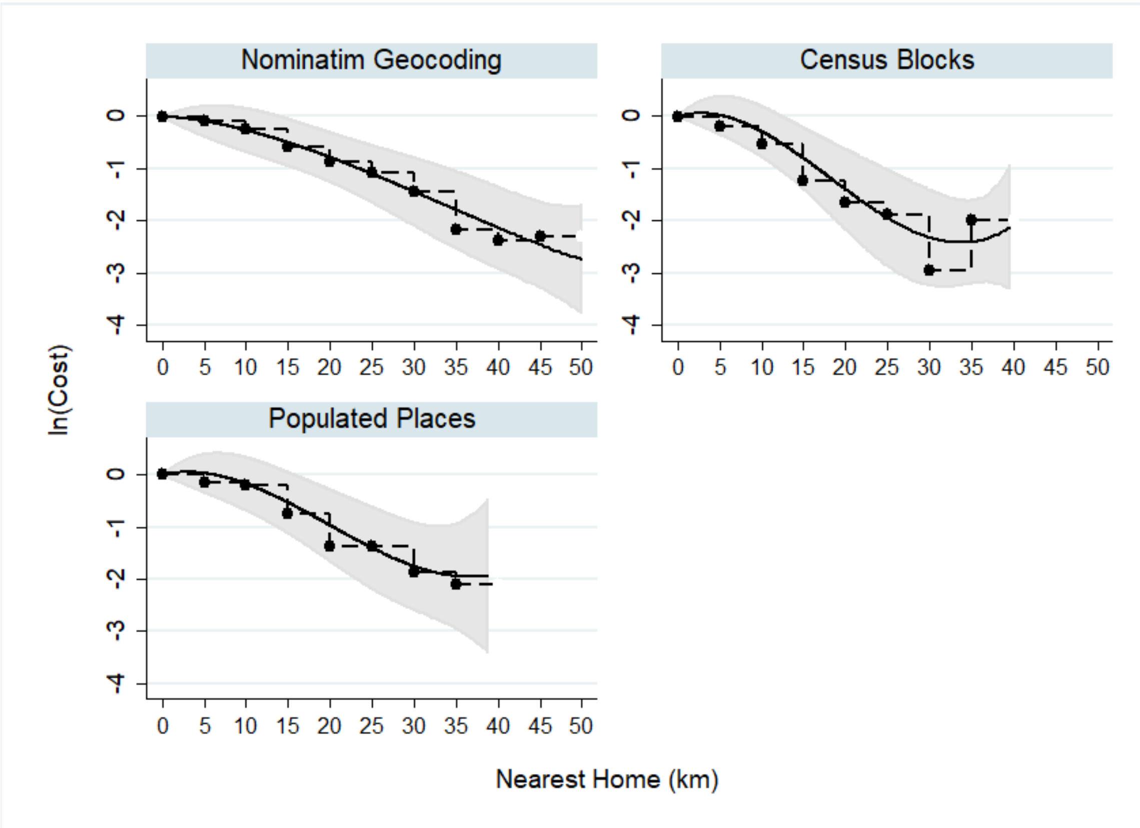
[40] Martinuzzi et al. (2015) describes one approach in detail, including how raw Census blocks are processed to remove portions that overlap public land and other steps.

Appendix Table 7: The Advantage of Parcel-level Data: Census Blocks in High-Cost Areas are Large

	Area in km^2	
	All Populated Census Blocks	Highest Decile of Firefighting Cost
Mean	1.2	6.6
p90	0.9	13.8
p95	3.0	27.6
p99	22.8	95.6
N	415,636.0	41,585.0

Notes: This table shows the distribution of areas for Census blocks, in square kilometers. Column (1) includes all 2010 Census blocks with greater than zero housing units. Column (2) includes the 10% subset with the highest average expected protection costs as identified in our study. While Census blocks tend to be small overall, the areas of greater interest for understanding firefighting costs are systematically larger. Data on Census block areas, housing counts, and locations are from the U.S. Census Bureau.

Appendix Figure 4: Cost by distance to nearest home



Notes: Each panel estimates the impact of nearest home distance, as measured using three different methods of locating homes, on log suppression cost. "Nominatim Geocoding" uses the geocoding and backstop method described in paper. "Census Blocks" uses Census block centroids. "Populated Places" uses the location information given in the Census Populated Places dataset. Each regression includes national forest fixed effects, state by month-of-year fixed effects, and state by year fixed effects. Standard errors are clustered by national forest.

B.3 Calculation of the additional fire cost due to homes

Δ_i is a per-fire estimate of fire suppression costs that occur as a result of home presence, or the "additional fire costs". The estimate of Δ_i that we use follows from the estimates from the binned model in Section 5.1.

Specifically, let $\hat{p}_d$ be our estimate of the proportional change in costs due to the nearest home being located d kilometers away relative to the nearest home being located 40+ kilometers away (the distance above which firefighting costs no longer decrease in our step function and linear spline estimates). Using the binned statistical model in Section 5.1, we compute $\hat{p}_d$ applying the transformation described in Footnote 10 to the coefficient for the bin that contains d.

Then, letting F_i be the observed fire cost and C_i be the counterfactual cost (the cost of the fire had it occurred more than 40 kilometers away), note that the relationship between two can be written as $F_i = C_i(1+\hat{p}_d)$. The additional fire cost is $\Delta_i = F_i - C_i$. Substitute and rearrange to obtain the estimate for Δ_i in terms of F_i and $\hat{p}_d$:

$$\Delta_i = F_i \frac{\hat{p}_d}{1+\hat{p}_d}$$

C Comparison to Forest Service Accounting Data

Our main analysis makes use of publicly available data on suppression expenditures for U.S. Forest Service Fires. However, Gebert, Calkin, and Yoder (2007) write that the publicly available data on costs are less accurate than official expenditure data recorded in the USFS accounting system. Since the time of their writing, the addition of an accounting code (known as a "P-code") to the FAMWEB data has made this match somewhat more straightforward.

To check whether the results of our empirical exercise in section 5.1 are altered by the use of the more accurate accounting data, we submitted a Freedom of Information Act Request to the U.S. Forest Service for the accounting dataset. The dataset we obtained as a result of this processing includes suppression expenditures from 2003-2013 with a limited set of fields. Specifically, it includes the P-code, the amount of suppression expenditures for that code, and the year that those expenditures were billed. The following table summarizes yearly cost for 2004-2012 (2003 and 2013 are partially missing in the accounting dataset) for the FAMWEB data and the accounting dataset we obtain.

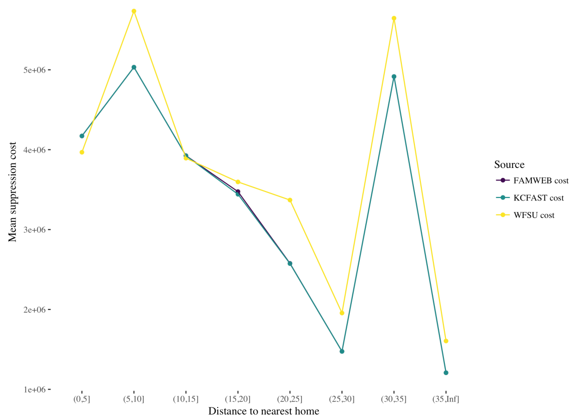
Appendix Table 8: Annual costs by suppression cost dataset

Year	FAMWEB	FAMWEB West	WFSU valid	WFSU all
2004	247	236	471	679
2005	271	262	440	768
2006	828	799	1,142	1,355
2007	978	923	977	1,263
2008	708	694	1,070	1,464
2009	401	394	682	840
2010	239	224	373	662
2011	475	436	623	1,251
2012	975	952	917	1,161
Total	5,122	4,920	6,695	9,442

Notes: All values in millions of dollars. First column includes all incidents in FAMWEB, second column includes only incidents in regions 01-06, third column includes only WFSU incidents with P-codes used for wildfire suppression-related costs. Specifically, the incident code begins with P*, where * is a number for the USFS region, and is followed by a 4 character alphanumeric code beginning with a letter, per USFS specification.

Next, we match the costs in the accounting dataset to the FAMWEB data using the P-code to identify whether the relationship between suppression costs and distance

Appendix Figure 5: Comparison of FAMWEB and accounting data: mean suppression costs and distance to nearest home

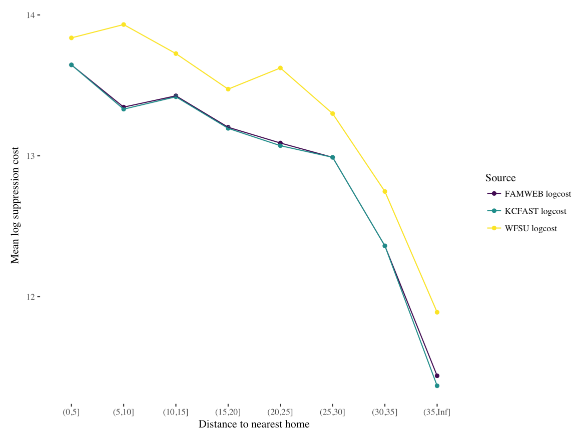


from homes is stable across the use of either source of cost data. We match from the P-code and year to the suppression expenditure data from FAMWEB. This match is not entirely straightforward: the guidelines over the issuance of P-codes and the proper accounting procedures have changed over the years, and many fires are submitted under the same P-code. In particular, large complex fires are often accounted for using the same P-code.[41] For the 997 fires in our FAMWEB dataset from 2004-2012, we are able to match 799 of these to the accounting dataset.

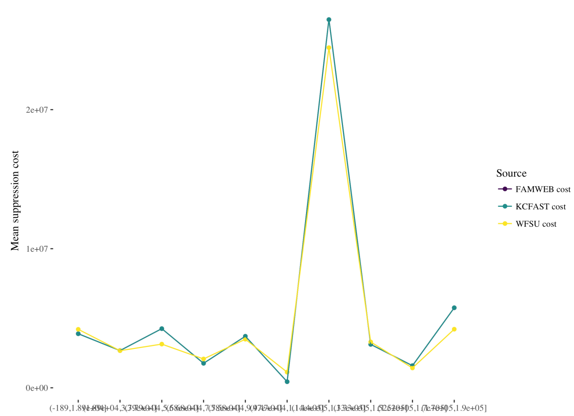
We estimate the relationship between fire cost and nearby homes for four sets of costs: A) FAMWEB costs for all fires in FAMWEB, B) FAMWEB costs for all 2004-2012 fires in FAMWEB, C) FAMWEB costs for fires that match to the accounting data, and D) accounting data costs for all fires that match to FAMWEB data. Figures 5, 6, 7, and 8 plot binned averages and sums of costs for each dataset on distance from nearest home and on number of homes within 30km. Although the sums differ due to the difference in the number of fires included for each set of data, the means have similar patterns. Our conclusions about the usefulness of the FAMWEB data are similar to those of Schuster, Cleaves, and Bell (1997), who wrote at the time that, "One of the purposes for our analysis of per-acre fire expenditures was to assess the quality of suppression expenditure estimates contained in the NIFMID database. These estimates are widely regarded as unreliable. However, the correlation between uncorrected, NIFMID-based expenditures and those from the accounting system is 0.85, a surprisingly high level."

[41]So-called "ABCD" fires, which are small, are also accounted for using a single P-code for each forest-year, but for our purposes this is not an issue since our focus is on incidents with more than 300 burned acres.

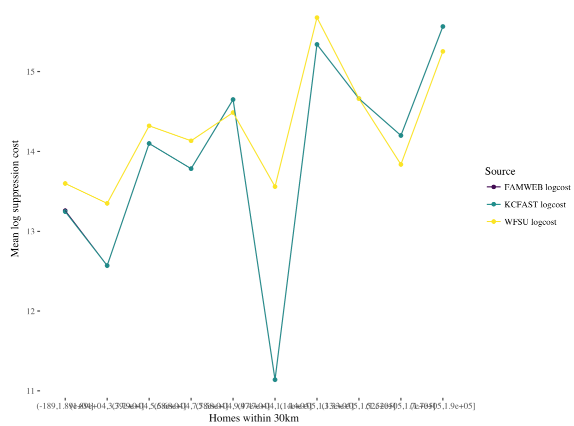
Appendix Figure 6: Comparison of FAMWEB and accounting data: mean log suppression costs and distance to nearest home



Appendix Figure 7: Comparison of FAMWEB and accounting data: mean suppression costs and number of homes in 30km



Appendix Figure 8: Comparison of FAMWEB and accounting data: mean log suppression costs and number of homes in 30km



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